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Essays on Macro-Finance and Uncertainty

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Essays on Macro-Finance and Uncertainty

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Scientifically, a dilettante's idea may have the very same or even a greater bearing for science than that of a specialist. Many of our very best hypotheses and insights are due precisely to dilettantes. The dilettante differs from the expert (...) only in that he lacks a firm and reliable work procedure. Consequently, he is usually not in the position to control, to estimate, or to exploit the idea in its bearings. The idea is not a substitute for work; and work, in turn, cannot substitute for or compel an idea, just as little as enthusiasm can. Both, enthusiasm and work, and above all both of them jointly, can entice the idea.

- Max Weber, *Science as a Vocation*

Abstract

This thesis consists of four independent chapters which study financial intermediaries and uncertainty from a macroeconomic perspective.

The first chapter provides new empirical evidence on the heterogeneity inside the financial intermediaries, namely the collection of commercial and shadow banks. Using a structural VAR model, we run two sets of experiments to explore the reaction of different banking sectors to different shocks. In the first experiments, we adopt short-run and proxy identification methods to check how they react to monetary policy shocks and discover that the same contractionary monetary shock triggers different responses in commercial banks and government-sponsored enterprises (GSEs). In the second experiment, we use the max share identification method to respectively determine the shocks that affect banks and shadow banks the most. The shocks likely differ highly across commercial banks and GSEs, but commercial and private shadow banks might be highly connected. These results confirm that understanding the heterogeneity and interconnectedness of the banking sector is essential for ensuring policy effectiveness and economic stability. Therefore, sector-specific supervision and regulations of the banking system are needed to monitor shocks propagation and amplification by the financial system.

The second chapter studies the impact of monetary policy on the credit allocation of globally operating banks. We develop an analytical framework for global banking based on a portfolio approach. In the model, global bank allocates their lending to both domestic and foreign borrowers for diversification benefits, but foreign lending comprises higher uncertainty due to cross-border frictions. Managing the uncertainty is costly and depends on banks' profitability driven by margins between lending and deposit rates. As a result, the effect of expansionary monetary policy on bank lending allocation is state-dependent. In times of low-interest rates and large balance sheets, a further cut in the interest rate decreases bank profitability and has opposite effects on domestic and foreign lending, thereby increasing home bias. Extending

the model to a dynamic general equilibrium setup with nominal rigidities, we find that with the portfolio re-balancing of the global banks, the prolonged period of low-interest rates is accompanied by a persistently high home bias, which is consistent with the empirical observation of the variations of bank home bias, and the overall effectiveness of monetary policy is compromised.

The third chapter empirically examines the home bias of globally operating banks. We collect quarterly data on a country level for the past two decades and compute the bank home bias index. Banks have exhibited a V-shaped home bias for many countries during the past two decades. Next, we analyze the drivers of banks' home bias using a structural vector autoregression model on US data. The results show that foreign uncertainty explains over forty percent of home bias variation, but not domestic uncertainty does not have a symmetric opposite effect. In addition, the monetary policy rate increases and then suppresses bank home bias. We extend the analysis to all the countries in our sample using a panel regression model and find similar patterns for uncertainty and monetary policy effects. Lastly, we study the cyclicality of bank home bias and confirm that the bias is negatively correlated with domestic output, indicating that domestic economic fluctuation can spill over to foreign countries through global bank lending quantity variations.

The last chapter explores different types of uncertainty shocks arising from different types of financial assets, with empirical evidence and a theoretical framework. First, by applying novel identification methods in structural autoregression (SVAR) models on different asset categories, we provide novel evidence on the heterogeneity in responses of real economic variables to uncertainty shocks. We show that uncertainty shocks generated by stock volatility have less impact than gold volatility in the post-crisis era. Both types of uncertainty shocks induce changes in the sentiment of both investors and households. Based on these findings, we sketch a simple theoretical framework that illustrates how fundamental uncertainty, asset-specific characteristics, and non-fundamental behavioral factors contribute to asset volatilities, which potentially accounts for the heterogeneities in the uncertainty shocks identified.

Acknowledgements

I started the Ph.D. study with a certain degree of blissful ignorance. Had I known the challenges I was about to face, I would probably have chosen not to embark on this scary journey, no matter how beautiful the scenery seemed at the harbor. To quote the lyrics from a song (which, unironically, is called The Scientist): *Nobody said it was easy; No one ever said it would be this hard.*

Nevertheless, the ship has sailed, and it turned out that I survived the difficulties I did not believe I could. It would not have been possible without the constant support from the TSE macro group. I'm deeply indebted to my supervisor, Patrick Fève, whose office door is always open whenever I have problems. His support and encouragement have been invaluable during difficult times. I am also grateful to Fabrice Collard and Christian Hellwig for their insightful comments and continuous guidance on my job market paper and other projects. I want to thank all the other macro group members: Tiziana Assenza, Martial Dupaigne, Eugenia Gonzalez-Aguado, Sumudu Kankanamge, Andreas Schaab, Nicolas Werquin, and all the macro students. This lively research group helped me navigate through the Ph.D. study and prepare for the future in the academic. I would also like to thank Matthieu Bouvard and Alexandre Gumbel for their detailed feedback on improving the paper and Nour Meddahi for his firm support and help throughout the job market.

Throughout this sometimes bumpy journey, I benefited tremendously from the company and support of my friends: Alae Baha, Hussein Bidawi, Luise Eisfeld, Yue Fei, Alipio Ferreira, Ivan Salles Fonseca, Dakang Huang, Fernando Stipanicic, Matthieu Tarbé, Ying Wang, and Yifei Zhang, and the list is not exhaustive. I am grateful for all the discussion, laughter, and lunches together. These experiences have made my time at TSE richer and more meaningful than I imagined. Special thanks go to Yifei Wang, whose unceasing encouragement and unconditional faith in me helped me through the darkest days in the last year of my Ph.D.; to Philipp Wangner, from whom I learned as much as I would from a teacher, our friendship withstands the grave challenge of being coauthors; and to Jun Yan, a great flatmate with whom I survived the whole Covid shutdown and the whole Ph.D., and a close friend whose support I can always count on. Her companionship and friendship are deeply treasured.

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Contents

Chapter 1

Shadow Banks vs. Commercial Banks: Different Responses or Different Shocks?

1.1 Introduction

Banking is a pervasive phenomenon, not something to be dealt with merely by legislation directed at what we call banks. Chicago economist Henry C. Simons made this sharp observation in 1936, and the message has not become obsolete. The past few decades have witnessed profound changes in the intermediary financial sector. Commercial banks ceased to be the dominant player, and a group of innovative financial institutions collectively known as shadow banking gradually took up shares in the market. While carrying the name "bank" and performing credit intermediation, this strand of financial intermediaries differs from traditional commercial banks in two significant ways. One difference is that shadow banks rely heavily on wholesale funding from the money market and other financial institutions, unlike commercial banks, whose primary funding source is retail deposits. Another striking feature of the shadow banking sector is the extensive use of financial tools and innovations, such as loan securitization. Their business model of original-to-distribute is thus very different from traditional banks' originate-to-hold nature.

Although it is straightforward to interpret shadow banks as a competitor to commercial banks, their relationship is more complicated than mere substitutions. For instance, commercial banks may hold a considerable amount of asset-backed securities (ABS) on their balance sheets as collateral, which are products of shadow banks. Another example would be commercial banks issuing guarantees for shadow bank liabilities. The twofold relation can be seen from the data. Figure 1.1 displays the quantity of loans originated by commercial and shadow banks. We can see that since the 1980s, during which financial deregulation and innovation took place, shadow banking loan origination outpaced commercial banks up until the Great Recession. However, the year-to-year growth rates of loans originated, shown in Figure 1.2, indicates that while the growth rates sometimes exhibit opposite directions, there are also periods with a high correlation between the two sectors. Complicated financial links and transactions among these banks can often obscure the interdependent structure of the system. Lacking a clear understanding of such intricacy of the system can undermine the effectiveness of the monetary and financial policy and lead to overlooking the systematic brewing risk.

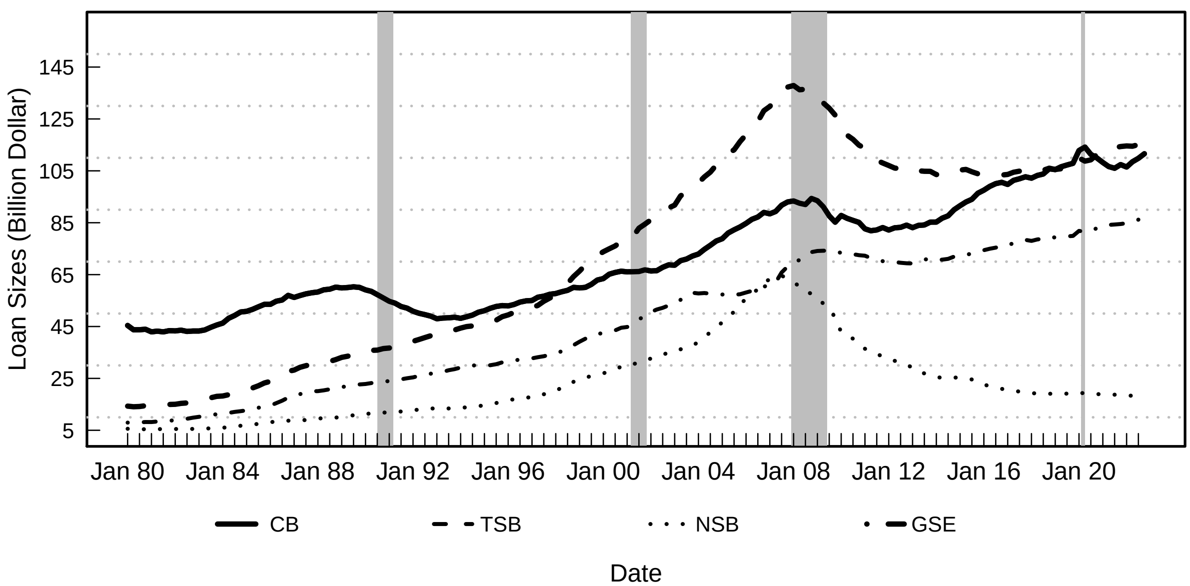

Figure 1.1: Loan Origination Quantity.

Notes: The plot shows the quantity of loan origination by four groups of banks, commercial banks, narrow shadow banks, government-sponsored enterprises, and total shadow banks. Details on the classification of the banks can be found in Appendix **??**. The loan quantity is in real terms (deflated using core CPI). Shaded regions denote the crisis periods.

Based on these observations, we ask the following questions in this paper: What drives the variations in the loan origination quantity of the banking sectors? Do they respond to the same shock differently, or do they respond to fundamentally different shocks? Our approach to answering these questions is thus also twofold. The first is to investigate the responses of commercial and shadow banks to shocks that are known to be influential to the banking sector,

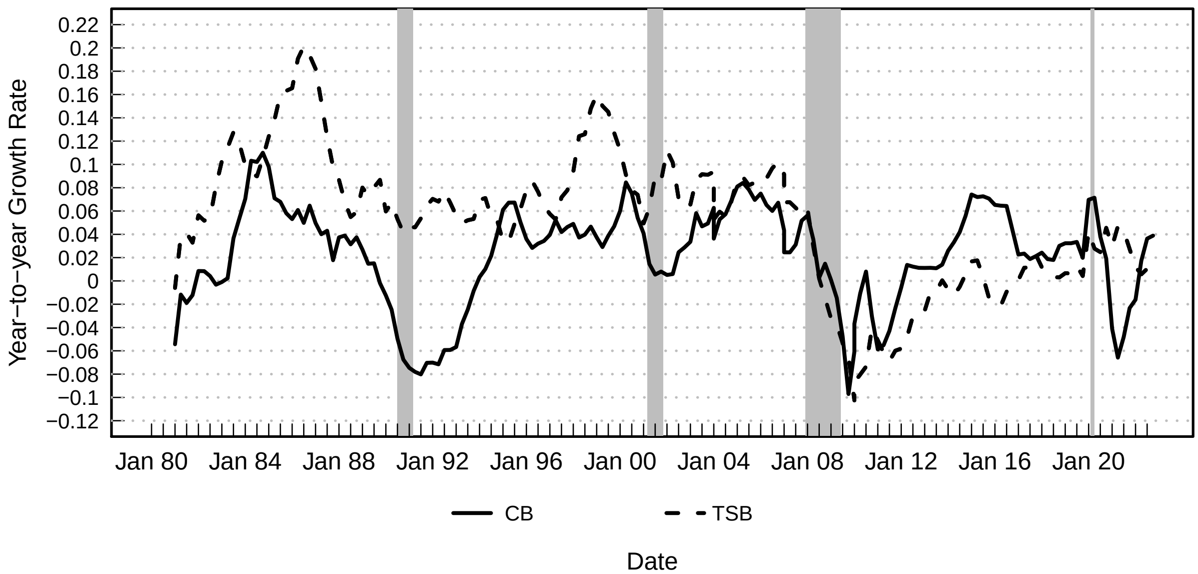

Figure 1.2: Loan Origination Growth Rate.

Notes: The plot shows the year-to-year growth rate of the quantity of loans from the commercial and shadow banking sectors. Shaded regions denote the crisis periods.

which, in our case, is monetary policy shock. The second starts from a different direction: We pin down the shocks that can explain most of the variations in each banking sector and then compare whether these shocks are alike.

To examine the responses of all banking sectors to one common shock, we start with the most apparent candidate: monetary policy. To what extent does monetary policy drive the variations of commercial banks and shadow banks? Understanding these questions is crucial for the comprehensive evaluation of the effectiveness of monetary policy. While banks and shadow banks are both financial intermediaries that supply credit to the economy, their distinct business models, that is, originate-to-hold versus originate-to-distribute, and differences in the types of loans they originate, imply that they have vastly different implications for economic growth. For instance, it determines whether the loans are directed more towards investments or consumption and whether the additional leverage is on safe borrowers or borrowers of less qualification. In addition, if the same policy rate adjustment leads to different responses from commercial and shadow banking sectors, the policy can have unintended consequences on financial stability. This is especially worrying if a contractionary policy tilts the balance towards the shadow banking sector. Since shadow banks are less regulated and rely more on the originate-to-distribute mode, they tend to invest in riskier projects where credit risks might occur. Moreover, shadow banks employ various short-term money market tools to fund long-term projects. Consequently, they are more prone to roll-over risks and bank runs. Most importantly, since the products of shadow banks, namely the securitized assets, are widely used as the private safe asset in the financial system, risks accumulated in the shadow sector can be highly contagious to other parts of the financial system, as made evident by the 2008 crisis.

Therefore, to answer this question, we employ structural VAR models with different identification methods. We find that monetary policy affects not only the size of financial intermediaries but also the relative shares of shadow banks and commercial banks in loan generation activities. Unlike commercial banks, shadow bank loans, in particular, government-sponsored enterprises' loans, increase after contractionary monetary shocks. Moreover, there is considerable heterogeneity within the shadow bank sector. The reactions remain robust after we add money market funds (MMFs) to the model, which is believed to be important for wholesale money supply. The results indicate that the heterogeneity in the asset side of the balance sheet of shadow banks is robust to changing conditions on its liability side. Interestingly, we find that MMFs react to contractionary monetary shock in the opposite way to commercial banks. The finding is consistent with recent observations by Xiao (2018), in which the author states that contractionary policy boosts MMFs but suppresses commercial banks' deposit collection.

Our finding shows that monetary policy shocks do not account for most bank loan variations. To identify the underlying shocks that are more influential to the banking sector, we proceed from the opposite direction. Instead of studying the reactions of banks and shadow banks to a known shock, we pin down unknown shocks that have been influential to these banking sectors, which are not necessarily the same for banks and shadow banks. Because the two sectors serve different groups of borrowers, the underlying shocks that drive the fundamentals for these two groups of banks could be different. For instance, since we know that shadow banks hold more securitized loans on their balance sheets, shocks that affect sectors such as real estate or the automotive industry, the loans of which are often securitized, may have a larger impact on the shadow banking sector than traditional banking. Therefore, this possibility calls for a completely different approach to shock identification for the SVAR model.

To be more specific, the idea is to identify shocks without imposing any restrictions on their nature or origins, nor do we presume the shocks identified for the two sectors turn out to be the same. The only criterion of identification would be the extent to which these shocks can explain the variations in banking sectors respectively. To achieve this goal, we adopt the max share identification method developed by Uhlig et al. (2004). With this approach, we solve the problem of shock identification as a maximization problem, which pins down the most influential shocks to each banking sector's loans.

Using this framework, we confirm the structural difference between commercial and government-sponsored enterprises, as there are fundamentally different shocks that can account separately for the forecast error variances of these sectors. The results also confirm the underlying link between private shadow banks and commercial banks, as the shock to commercial banks eventually got transmitted to the private shadow banking sector. We see that the shock that contributes the most to the commercial bank sector has a delayed impact on the narrow shadow banking sector but with no significant impact on the GSE sector. The shock for narrow shadow banks increases both commercial bank loans and GSE loans at a similar magnitude; the difference is that it impacts commercial bank loans contemporaneously, whereas the effect on GSE loans comes with a delay. The shock for GSE, however, does not significantly impact commercial or narrow shadow bank loans.

In addition, we compare the pre-crisis period to the post-crisis period and find significantly different patterns. The shocks that explain changes in GSE sectors have a considerable influence on commercial banks. On the contrary, the link between narrow shadow banks and commercial banks diminishes. Commercial bank shocks no longer produce or explain narrow shadow bank loan responses and vice versa. The results indicate that the interconnectivity of the banking industry has undergone a transformation after the Great Recession. Further examination is needed for close supervision and regulation to ensure the stability of the banking system and the financial sector.

Literature Our research mainly relates to three strands of Literature. The first is the study on the interaction between monetary policy and financial intermediaries. Adrian and Shin (2009) provides a general description of how market-based credit intermediation becomes increasingly essential. Adrian and Shin (2008) documents empirical evidence of short-term interest rates affecting broker-dealer asset growth. Adrian and Shin (2010) develops a model with a value-at-risk constraint to show how monetary policy rate affects risk pricing and stress the role of short-term interest rate in determining the balance sheet growth of financial intermediaries. Bianchi and Bigio (2017) develops a model that explicitly accounts for the liquidity transaction between banks on the inter-bank market and articulates how monetary policy determines banks' choice between lower liquidity shock and higher profits. Heider et al. (2015) also focuses on the inter-bank market and liquidity, emphasizing asymmetric information about asset quality, which gives rise to counterparty risk. Our study may serve as an empirical examination of the impact of monetary policy on the liquidity situation in the financial intermediaries sector.

The second strand is the study of the shadow banking sector, particularly its role in monetary policy effectiveness. On the one hand, the existence of the shadow banking sector can undermine the effectiveness of monetary policy (Estrella, 2002), as is the case with China's quantitative monetary policy (Chen et al., 2017). On the other hand, monetary policy is also one of the driving force of the dynamics of the shadow banking sector, as shown by Nelson et al. (2018) on how contractionary monetary policy increase shadow banking activities. Moreover, shadow banking may indirectly affect monetary policy outcomes by changing commercial banks' liquidity conditions. Loutskina (2011) finds that securitization activities can sabotage the efficacy of open market operations, as banks now have liquidity assets other than reserves. Besides shadow banking activities involving securitization, shadow banks in the deposit market, namely money mutual funds, also affect monetary policy transmission. Xiao (2018) finds that during monetary policy tightening, liquid deposits created by shadow banks increase sharply. This paper attributes to this strand of studies by providing a more detailed decomposition of shadow banks and a separate examination of banks and shadow bank loans.

The last strand of Literature is the role of monetary policy in financial stability. Ever since the Great Recession, research on monetary policy has shifted from focusing on a rule that targets only output gaps and inflation to have a more general framework, acknowledging that monetary policy may directly affect financial stability. Borio and Zhu (2012) gives a comprehensive review of the possible channels through which such a risk-taking channel of monetary policy operates and its correlation with more traditional credit channels. Various empirical studies have proved the existence of such a channel in the banking system. These studies are followed by a heated debate of whether monetary policy should have a macroprudential goal, or at least "leaning against the wind" (Svensson (2018)). Our paper provides evidence for this debate, showing how monetary policy may inevitably change the game for participators in credit intermediation, therefore, can have a potential financial stability impact.

Layout The rest of the paper is organized as follows. Section 1.2 introduces the data we use and several stylized facts about the shadow banking sector. Section 1.3 gives the empirical methods and results of the first approach, showing how monetary policy has a different impact on different financial intermediaries. Section 1.4 introduces the second approach using max share identification and documents the results of shock identified for each banking sector. Section 1.5 concludes.

1.2 Data and Stylized Facts

1.2.1 Definition

Before diving into the analysis, we need to define commercial and shadow banks of interest and introduce the key features of the relationship between the two. As briefly stated in the introduction, a broader definition of shadow banks should include two categories of financial intermediaries: the first, which we refer to as *liability-side shadow banks*, engage in retail deposit competition with commercial banks but invest mainly in risk-free or low-risk liquidy assets. Examples of this type of shadow bank include money market funds[1]. The second type, which we refer to as *asset-side shadow banks*, or just shadow banks in this paper, rely on wholesale funding and engage in loan origination and other forms of risky lending, especially asset securitization. In this paper, we narrow the scope of our analysis of shadow banks to the second type and focus on banks' lending behaviors, not liability structure. For a more detailed description of the banking sectors, see Appendix 1.7.1.

1.2.2 Measurement

The data we use for this research is mainly U.S. Financial Account data, which consists of a detailed description of the transactions and levels of all financial assets and liabilities in the U.S. financial market. The data provided is classified both by sector and by instrument. The literature has two consensuses of measuring shadow banking, which we will refer to as total and narrow shadow banking. The former is used in paper Adrian and Shin (2010), and the latter in Gertler et al. (2016). Table 1 shows the eight institutions classified into total shadow banking and their corresponding labels in the data set. Adrian and Shin (2010) narrows the definition of shadow banks down to the first three of these eight institutions. Therefore we will refer to this definition as Narrow Shadow Banking (NSB). Nelson et al. (2018) definition further includes Government-sponsored enterprises (GSE) and GSE mortgage pools, and we will refer to these two as Total GSE.

[1] Kairong Xiao (2018)

To show that our definition of Narrow Shadow Banking and Total GSE pick up the majority of loan generation by the shadow banking sector, we plot the composition of loan generation in the shadow banking sector over the years in Figure 1.24 in Appendix 1.7.2. Among all the institutions in the shadow bank category, GSE, ABS Issuers, and Finance Companies account for a substantial share of loan generation. However, their trends are quite different. We can see that the loans by ABS issuers started snowballing in the 1980s and taking over the share of finance companies. In contrast, GSE loan size stayed quite stable[2].

1.2.3 Stylized Facts

To examine the heterogeneity inside the shadow banking sector, we follow our classification of narrow shadow banks (NSB) and government-sponsored enterprises (total GSE) and compute the loan growth rates of these institutions respectively. The results are shown in Figure 1.3 and Figure 1.4. As we can see, the year-to-year growth rate is similar to the general trend but departs from time to time. The trend for total GSE has never been quite the same as commercial banks. Their trends seem to be going in opposite directions, particularly during the years before the crisis. We can see a more precise cut for narrow shadow banks: before the 1980s, they were highly synchronized with commercial banks. This is hardly surprising, as Figure 5 shows that during this period, the size of narrow shadow banks is dwarfed by commercial banks. However, as the growth picked up pace during the 1980s, the synchronization was no longer sustained. Narrow shadow bank loans have become more volatile and have shorter cycles than commercial bank loans. Furthermore, they almost always have a higher growth rate, which again reversed right before the crisis as shadow bank loans took a nose dive. To sum up, the two components of shadow banks have different characteristics, which we will investigate in more detail in the following sections.

There is considerable heterogeneity inside shadow banking sector. Following our classification of narrow shadow banks (NSB) and government-sponsored enterprises (total GSE), we compute the loan growth rates of these institutions. The results are shown in Figure 9. As we can see, the year-to-year growth rate are similar in general trend, but departs from time to time. Trend for total GSE has never been quite the same as that of commercial banks. Their trends seems to be going into opposite directions in particular during the years before the crisis. For narrow shadow banks, we can see a clearer cut: before 1980s they are highly

[2] The sudden increase in GSE loan size after 2008 is due to the change in accounting rules in which GSEs moved mortgage pools into consolidated balance sheets.

synchronized with commercial banks. This is hardly surprising, as Figure 5 shows that during this period the size of narrow shadow banks are dwarfed by that of commercial banks. However, as the growth picked up pace during the 1980s, the sychronization is no longer sustained. Narrow shadow banks loans seem to have become more volatile and have shorter cycles than commercial bank loans. Furthermore, they almost always have higher growth rate, which again reversed right before the crisis as shadow bank loans took a nose dive. To sum up, the two components of shadow banks indeed seem to have different characteristics, which we will investigate in more detail in the following sections.

1.3 Monetary Policy Shock

1.3.1 Model Specification

In order to identify monetary policy shocks and estimate their effects on the banking sectors, we estimate the following VAR:

$$y_t = B_0 + \mathbf{B}_1 y_{t-1} + \cdots + \mathbf{B}_p y_{t-p} + u_t \qquad t = 1, \cdots, T \tag{1.3.1}$$

where y_t is a $n \times 1$ vector of endogenous variable, B_0 is a vector of constant, $\mathbf{B}_1$ to $\mathbf{B}_p$ are $n \times n$ coefficient matrices, and u_t is reduced-form errors. The model can be estimated by standard ordinary least squares (OLS). Define ϵ_t as the vector of the orthogonal structural shocks with unit variances. We assume that the relationship between the structural shock and the reduced-form innovations is given by $u_t = \mathbf{A}\epsilon_t$. To identify the monetary policy shock, we need additional assumptions to pin down the matrix A.

1.3.2 Identification

We identify monetary policy shocks using two different methods: short-run identification and proxy identification.

Short-run Identification With Short-run identification, we impose restrictions on which contemporaneous variables may be affected by each exogenous shock. Following the standard practice proposed by Christiano et al. (2005), we include output, inflation, and monetary policy rate in the vector of endogenous variables. More importantly, since our goal is to analyze the responses of banks to monetary policy shock, we add to the macroeconomic variables the balance sheet components of the three banking sectors that we are interested in, namely commercial banks, narrow shadow banks, and government-sponsored enterprises (GSE)[3]. Under this specification, the assumption is that the monetary shock will react to changes in GDP and inflation but not to the other balance sheet variables[4].

Under this assumption, the model is identified by performing Cholesky decomposition to the variance-covariance matrix, $\Sigma = \mathbf{A}'\mathbf{A}$, where $\mathbf{A}$ is a lower-triangular matrix that pins down the relationship between structural shocks ϵ_t and reduced-form errors u_t, i.e., $u_t = \mathbf{A}\epsilon_t$.

Proxy Identification The assumption that monetary policy shock does not respond to contemporaneous innovations to banking sector balance sheet variables may be too restrictive. To relax this recursive restriction, we introduce a second identification method, which is proxy identification with the two-stage least-squares (2SLS) method following Stock and Watson (2012) and Mertens and Ravn (2013).

The identification assumption is as follows. Denote ϵ_t^p as the structural of interest, which, in our case, is the monetary policy shock, and denote $\boldsymbol{\epsilon}_t^q$ as a vector containing the rest of the structural shocks. Similarly, denote u_t^p as the reduced-form residual for the monetary policy and $\boldsymbol{u}_t^q$ as that of the other variables. Suppose that there exists an additional exogenous variable Z_t that satisfies the following conditions

$$E\left[Z_t \epsilon_t^p\right] = \phi, \quad E\left[Z_t \boldsymbol{\epsilon}_t^{q'}\right] = 0 \tag{1.3.2}$$

where $\phi \neq 0$. With this exogenous variable, we can use the 2SLS method to identify the monetary policy shock. In the first stage, we regress u_t^p on Z_t to obtain the fitted value $\widehat{u}_t^p$ that contains the information from the structural shock solely; in the second stage, we regress all other reduced-form errors $\boldsymbol{u}_t^q$ on $\widehat{u}_t^p$

$$\boldsymbol{u}_t^q = \psi_0 + \boldsymbol{\psi}_1 \hat{u}_t^p + \xi_t \tag{1.3.3}$$

The regression coefficient $\boldsymbol{\psi}_1$ is equal to $\frac{\boldsymbol{a}_{qp}}{a_{pp}}$, where $\boldsymbol{a_p} = (a_{1p}, a_{2p}, ..., a_{np})'$ is the vector in the matrix $\mathbf{A}$ that corresponds to the monetary policy shock, and $\boldsymbol{a}_{qp}$ the component of this vector that excludes the coefficient for variable p. Given the ratio between the entries, $\frac{\boldsymbol{a}_{qp}}{a_{pp}}$, further

[3]Detailed description of the variables we used can be found in Table 4.12.

[4]Regarding ordering the balance sheet variables, there has yet to be a consensus on the channel of influence among different banking sectors. To start with, we assume the commercial banks move first, followed by narrow shadow banks and GSEs. We change the order to check the robustness of the assumption.

computation using the variance-covariance matrix Σ pins down the values[5]. The SVAR model is then partially identified, as we recover one column $\boldsymbol{a_p}$ of the matrix $\mathbf{A}$ that pins down the monetary policy shock.

To proxy monetary policy shocks, we use the data from Gertler and Karadi (2015) and Nakamura and Steinsson (2018). Following Gertler and Karadi (2015), we use one-year constant maturity yield on U.S. treasury securities as the monetary policy indicator. The start and end dates of the proxy variables are given in Appendix 1.7.3.

1.3.3 Results

Before studying the impact of monetary policy shock on banking sectors, we first run an SVAR model that includes in y_t only the standard macroeconomic variables and one risk indicator to examine the behavior of the monetary policy shock identified using two methods[6]. Figure 1.5 shows the impulse responses of the variables to the monetary policy shocks identified. Figure 1.6 gives the forecast error variance decomposition. As can be seen from the figure, the monetary policy shocks identified using short-run and proxy identification generate similar responses from the real output. However, the response of inflation exhibits a price puzzle, i.e., price increases in the short run following the unexpected monetary policy tightening. Meanwhile, the risk appetite of the market, reflected by the excess bond premium (EBP), an index developed by Gilchrist and Zakrajšek (2012), does not react to the shock identified. In contrast, the monetary policy shock identified using the proxy approach mitigates the price puzzle, as inflation decreases on the impact of the policy shock. Moreover, it induces a significant increase in the excess bond premium, reflecting that the risk-taking appetite of the market decreases after the monetary policy tightening. The results are consistent with the findings of Gertler and Karadi (2015).

Nevertheless, the forecast error variance decomposition shows that the short-run monetary shock can explain over eighty percent of the forecast error variance on impact. The proxy shock, however, only explains forty percent, less than half of the variances from the short-run monetary shock, indicating that the shock might not capture all the effects of a monetary policy shock. The explanatory differences can arise from the construction of the proxy variables used in the identification. Since the proxies are obtained using high-frequency methods

[5] For a detailed description of the computation on the proxy identification, see Appendix 1.7.3.

[6] To keep consistency, we also use one-year constant maturity yield on U.S. treasury securities as the monetary policy indicator in the short-run identification. The results are still robust when using federal funds or shadow rates instead of one-year bond return.

applied to a short time window around the FOMC announcements, they might not capture the complete responses to monetary policy shock. However, the proxy shock does explain significantly more responses from the excess bond premium.

We now add to the endogenous variables the loan origination of different banking sectors. Figure 1.7 gives the impulse responses to the shock under two identification schemes. Figure 1.8 gives the forecast error variance decomposition[7]. The results show that the contractionary monetary policy shock does not significantly impact commercial banks' loan generation. For the shadow banking sector, however, the policy has heterogeneous effects: Narrow shadow bank loans do not jump on impact but decrease gradually after the policy, whereas GSE loans increase right after the shock occurs and then gradually attenuate. Different responses from the three banking sectors confirm that monetary policy has not only a quantity effect but also a composition effect on the credit supply of the financial intermediaries. Following a policy shock, loan origination by different financial intermediaries can go in different directions, resulting in a relative increase in GSEs loans in the total amount of loans originated.

This heterogeneity in shock responses arises from two potential channels. Recent research on monetary policy transmission highlights two novel mechanisms, namely the liquidity and risk-taking channels, which can contribute to the phenomenon. The liquidity channel stresses monetary policy's effect on banks' demand for liquid assets. Shadow banking sectors play a crucial role in satisfying financial intermediaries' demand for liquidity by providing securitization products, such as asset-backed securities (ABS) and mortgage-backed securities (MBS). With the pooling and tranching process on individual loans, shadow banks produce assets with different levels of riskiness, the safest of which receive top ratings and are thus perceived as a good substitute for traditional liquidity, such as Treasury bills[8]. This consensus paved the way for these asset-backed securities to be used as collateral to secure short-term funding through money market tools like repurchase agreements (Repo) and asset-backed commercial papers (ABCP). Thus, when unexpected monetary policy tightening deteriorates the liquidity conditions and slows down loan-generating activities, shadow banking sectors, whose business model is originate-to-hold rather than originate-to-distribute, may experience an increase in demand for their products as high-quality collateral to secure liquidity after the contractionary monetary policy shock, which leads to more loan origination by shadow

[7] We also perform the same exercise on the whole sample period from 1980 to 2022, and the key findings remain largely unchanged. Figure 1.9 shows the impulse responses of the variables to the monetary policy shocks identified. Figure 1.10 gives the forecast error variance decomposition.

[8] Systematic tail risks of asset-backed securities were brought to public attention and under scrutiny by the regulatory authority in the 2008 crisis.

banks.

The second channel, the risk-taking channel, can explain the difference between narrow shadow banks and GSEs. As seen in Figure 1.7, the proxy identification of monetary policy yields more significant responses from risk-taking appetite, as reflected by the excess bond premium. At the same time, we observe a more significant increase in GSEs loans but not commercial banks or narrow shadow bank loans. The responses from EBP confirm the risk-taking channel of monetary policy, which impacts the concerns over the vulnerability of securitization products. Although both narrow shadow bank and GSE sectors engage in securitization activities, the products of GSEs are perceived to be safer than that of the narrow shadow banks[9], due to two main reasons. First, although GSEs are generally not under the federal government's direct control, they may still be subject to more policy influence and are considered safer than other shadow banks due to implicit guarantees from the government. At the same time, narrow shadow banks are of private ownership and have guarantees only from commercial banks or other large financial institutions. Second, this difference also arises from the type of loans these institutions originate. GSE loans consist of mostly conforming loans, such as mortgages that consist of housing and farmland, while the loan types of narrow shadow banks are of various types, including consumer loans like auto loans. The quality of the loans is also more susceptible to risk appetite.

To sum up, examining the responses to monetary shock and the reason behind the difference sheds light on the underlying structure of financial intermediaries. The results suggest that monetary policy can have unintended consequences on the composition of loan origination from different financial intermediaries. It is essential to consider this heterogeneity in the policy responses when estimating the impact of monetary policy on credit supply and the overall stability of the financial system.

Nevertheless, as can be seen from the forecast error variance decomposition in Figure 1.8, monetary policy shocks identified using either of these approaches do not explain much of the variances of bank loan variations. While the monetary policy shock has moderate explanatory power over narrow shadow bank loans (above thirty percent), it explains only less than ten percent of the variations for commercial and shadow banks. This result suggests that other shocks are more prominent in affecting banking sector dynamics, and these shocks might not be the same across sectors. In the next section, we will examine these differences by looking

[9]The difference reflects the hierarchy within the shadow banking sector. As pointed out by Pozsar (2014), a division exists between a public-private and a purely private shadow banking subsystem. While the products are essentially the same, this difference is still picked up by the market participators and reflected in the trends.

for sector-specific shocks that can explain the different driving forces of different banking sectors.

1.3.4 Robustness

Effects of the Money Market Funds (MMF)

One possible concern of our baseline model is that it leaves out the wholesale money supplier, another source of shadow banking funding. Xiao (2018) states that MMF provides a good proxy of the amount of funding for shadow banking. If an increase in policy rate changes money market conditions, which affects shadow banks' wholesale money supply, then leaving it out may bias the results of the VAR model. In order to test this channel, we add Money Mutual Funds, the principal investor in the money market, into the model. Figure 1.11 shows the impulse responses of the variables to the monetary policy shocks identified. Figure 1.12 gives the forecast error variance decomposition.

As can be seen from the figure, MMF's value first decreases and then increases after the contractionary policy. The initial drop can be attributed to a general tightening of the liquidity environment. The subsequent increase confirms the findings of Xiao (2018), i.e., that policy rate increases cause MMFs to increase their return rate higher than commercial banks, thereby attracting more deposits. The responses of the macroeconomic variables do not differ significantly from the model without MMF, with a slightly more decrease in output. The bank loan variables are also primarily preserved, although the decrease in commercial and narrow shadow bank loans in the following periods after the shock becomes more significant. However, after adding MMF to the model, the share of FEV explained by the proxy monetary policy shock on commercial and narrow shadow banks becomes much higher than the model without MMF. This difference indicates that the vital transmission of monetary policy shock on bank loans is through the liability side competition. Overall, the results confirm that the previous findings are robust to changes in the liability side of the banking system.

Effect of the Mortgage=backed Securities (MBS)

As stated in the previous section, one potential explanation for the difference in loan generation is that the difference reflects the difference in the composition of loans in different sectors. The surge in GSEs could be due to the higher demand for mortgage-backed security, which might be perceived as a safer asset than ABS. To test this hypothesis, we take out the subgroup of loans, namely the category Mortgage, instead of total loans in the balance sheets. If this hypothesis is true, we should observe an increase in mortgages in both narrow shadow banks and GSEs. The results do not back up the story. The mortgage of narrow shadow banks experienced a drop right after the shock and took time to recover to the previous level. The mortgage of commercial banks also drops. This pattern suggests that it is different from the mortgage category that matters. Those who originate and securitize the mortgage might play a more critical role in the evaluation of its soundness.

1.4 Sector-specific Shocks

In this section, we shift from studying the response of different banking sectors to the same shock to separately pinning down the most influential shock for each sector while allowing for the possibility that the shocks can differ across sectors. To this end, we adopt the max-share identification approach introduced in Uhlig et al. (2004). The method has been used to study TFP shocks (Francis et al., 2014) with finite horizons and news shocks on TFP production (Barsky and Sims, 2011; Kurmann and Sims, 2017).

The merit of adopting this method to study banking sector shocks is twofold. First, it allows us to focus on different banking sectors while keeping track of their connections. While the shock is pinned down as the one that has the maximum explanatory power for the variations of one particular sector, by observing the response of other sectors triggered by this particular shock, we can thus infer the underlying connections between the objective sector and this one that generates this shock. Second, applying it to studying different banking sectors allows us to analyze more mid to long-run drivers of the variations in different banking sectors. When using this method, we can choose the length of the reaction period we seek to explain. This flexibility is crucial, as we can determine whether the shock has an immediate reaction or has an impact in the relatively long run that we seek to capture.

1.4.1 Model Specification

To keep consistency, we have the same model specification and variable choices as in the previous section. Define y_t as a vector of endogenous variables containing three macro variables (output, inflation, and monetary policy) and three balance sheet variables of three banking sectors (commercial bank, narrow shadow bank, and GSE). The model is again given by

$$y_t = B_0 + \mathbf{B}_1 y_{t-1} + \cdots + \mathbf{B}_p y_{t-p} + u_t \qquad t = 1, \cdots, T \tag{1.4.1}$$

where u_t are the reduced-form errors with variance covariance matrix Σ, $\Sigma = AA'$. Take $\tilde{A}$ to be the Cholesky decomposition of matrix Σ so that $\tilde{A}\tilde{A}' = \Sigma$, then for any decomposition A of the matrix Σ, there exists an orthonormal matrix Q, such that $A = \tilde{A}Q$. This notation allows us to prepare for the identification using the max share approach.

1.4.2 Identification

The object of the max-share identification approach is to find a shock that has the maximum explanatory power of the variations of the targeted variable. The criterion of explanatory power is the contribution to the forecast error variance (FEV). Since the forecast error variance can be viewed as the sum of the variance of forecast errors caused by different shocks, the contribution of one particular shock can be measured by computing the ratio between the forecast error variance due to this shock over the total FEV.

The h step ahead forecast error of variable i can be written as

$$y_{i,t+h} - E_{t-1} y_{i,t+h} = \sum_{l=0}^{h} B_l \widetilde{A} Q \epsilon_{t+h-l}$$

and variable i's forecast error variances over a horizon of h periods that is driven by shock j is given by

$$\Omega_{i,j}(h) = \frac{\sum_{l=0}^{h} \mathrm{B}_{i,l} \widetilde{\mathrm{A}} q q' \widetilde{\mathrm{A}}' \mathrm{B}'_{i,l}}{\sum_{l=0}^{h} \mathrm{B}_{i,l} \Sigma_u \mathrm{B}'_{i,l}}$$

where q is one column of matrix $\mathbf{A}$ that corresponds to the shock j[10].

Under the max-share approach, the column q is not defined by exogenous assumption; Rather, it is determined by the following maximization problem

$$\max_q \sum_{h=0}^{k} \Omega_{i,j}(h)_{ii}$$
$$\text{s.t.} \quad q'q = 1$$

That is, vector q corresponds to a shock that can account for most of the forecast error variance

[10]There is, however, no restriction that has to be a single column. We can choose to maximize over $Q = [q_1, q_2]$ to identify two shocks. To start with, we narrow the scope of our analysis to a single shock.

of variable i up to h period. The model is then partially identified since we have pinned down as the solution to the optimization problem one column q of the matrix $\mathbf{A}$. After feeding these shocks back into the model and interpreting the impulse responses generated by this shock, we can make further inferences on the nature of this shock.

In the context of our problem, the targeted variable is bank or shadow bank balance sheet components. Our goal is to identify shocks that can explain most of the forecast error variance of commercial banks (CB), government-sponsored enterprises (GSE), and narrow shadow banking (NSB), respectively, over some finite horizon. Therefore, we run two sets of exercises using different endogenous variables y_t. For the simple setup, y_t includes only core variables, i.e., the total asset or loans of the banks; For a complete setup, y_t contains three macro variables (output, inflation, and monetary policy) and three balance sheet variables of three banking sectors (commercial bank, narrow shadow bank, and GSE).

1.4.3 Banking Sector Shocks

To start with, we have the following setup for the baseline specification. We run the SVAR and solve the maximization problem using bank loans from 1980 to 2007 as our targeted variable. All VAR models use four lags. We choose a relatively short horizon of two years (8 quarters) to explain. Figure 1.13, 1.15, and 1.17 shows the FEVD of the shocks identified using max share approach to the commercial bank, narrow shadow bank, and GSEs respectively.

As seen from Figure 1.13, the shock identified can explain up to approximately all of the forecast error variances of the commercial bank sector. What is noteworthy is the reactions of the rest of the banking sector. We see that the shock that contributes the most to the commercial bank sector has a delayed impact on the narrow shadow banking sector but with no significant impact on the GSE sector.

The results provide evidence for the connection between commercial and narrow shadow banks. After the shock boosts commercial bank loans, commercial banks may seek to expand their loan generations further but are bound by capital or liquidity requirements regulations. Providing guarantees for narrow shadow banks that do the lending may serve as one way to circumvent this restriction, through which commercial banks expand lending while keeping the loans off-balance sheet for commercial banks. This implicit link leads to a delayed surge of NSB loans after commercial banks' space for loan origination has saturated. However, this effect does not extend to the GSEs, as they are perceived to be different from private financial institutions in the market. GSEs and commercial banks may be subject to different fundamental shocks and do not have close connections.

Figure 1.13 confirms our hypothesis. The figure shows that when the same method is applied to the GSE sector, the shock that explains forecast errors in GSE has little impact on the rest of the banking sectors. Figure 1.15 displays the result of the exercise using the narrow shadow banking sector. While the influence on GSE loans is still limited, narrow shadow banking shock impacts commercial bank loans, albeit with some delay.

We now turn to the impulse responses from the sector-specific shocks, as shown in Figure 1.14, 1.16, and 1.18. We can see that patterns of the responses vary across sectors. The commercial bank shock boosts narrow shadow bank loans but does not significantly impact GSE loans. The shock for GSE, however, does not significantly impact commercial or narrow shadow bank loans. The shock for narrow shadow banks increases both commercial bank loans and GSE loans at a similar magnitude; the difference is that it impacts commercial bank loans contemporaneously, whereas the effect on GSE loans comes with a delay. The responses align with our interpretations of the forecast error decomposition, but we need further examinations with macroeconomic variables to pinpoint the exact nature of the identified sector-specific shocks.

1.4.4 Post-crisis Behavior

As robustness checks, we perform the following exercises. First, we perform the same analyses over the whole sample period, e.g., from 1980 to 2022, to see if the same patterns are preserved before and after the Great Recession. Figure 1.25, 1.29, and 1.33 in Appendix 1.7.3 show the max share shock computed over the sample period from 1980 to 2022 using the commercial bank, narrow shadow bank, and GSE loans respectively. Second, we focus on a shorter sample period from 2007 to 2022. Figure 1.26, 1.30, and 1.34 in Appendix 1.7.3 show the results.

Comparing the differences across sample periods, we can see that while the results are robust to the change to the whole sample (2008 to 2022), once we single out the post-crisis periods, the patterns are significantly different, especially for GSEs. The shocks that explain the variations in GSE sectors have a significant impact and substantial explanatory power on commercial banks. On the contrary, the connection between narrow shadow banks and commercial banks becomes smaller. Commercial bank shocks no longer induce or explain the responses of narrow shadow bank loans, and the narrow shadow bank shocks also play little role in the variations of commercial bank and GSE loans. The results suggest structural changes in the interdependence within the banking sector after the Great Recession. On the one hand, commercial and narrow shadow banks become more independent of each other, which might be attributed to the changes in regulatory policy aiming at curbing systematic risks caused by asset-backed securities. On the other hand, the commercial and GSEs loans start to comove to a greater extent. Although the GSEs loans and their MBS products are much safer in nature, the synchronization can still generate potential danger for financial stability if banks rely on MBS collectively for liquidity needs.

1.4.5 Future Directions

Orthogonalized Shocks

So far, in our specification, we do not assume the shocks identified using one banking sector to be orthogonal t shocks that also affect the other banking sectors contemporaneously. We use the max share identification approach with an additional constraint to obtain clean results by purging off this common shock effect.

$$\begin{aligned} \max_q \sum_{h=0}^{k} \Omega_{i,j}(h)_{ii} \\ \text{s.t.} \quad q'q = 1 \\ q(i) = 0 \end{aligned}$$

Shock Comparison

In this section, we explore further the natural of these sector-specific shocks by running the same exercises on a complete model incorporating macroeconomic variables.

1.5 Conclusion

This paper seeks to provide some empirical investigation into the increasingly complex and intertwined financial intermediary system that we have today. The evidence found proves that the heterogeneity inside this sector indeed matters. On the one hand, our first sets of results show that such heterogeneity can induce vastly different responses to the same shock, which, in our case, is the same monetary policy shock. When facing a contractionary monetary policy shock, commercial banks decrease loan generation. In contrast, shadow banks, particularly government-sponsored enterprises, do not exhibit the same pattern and even increase slightly after the shock. The results indicate yet another unintended consequence of the policy, namely tilting the balance between bank and shadow banks, and thus calls for the monetary authority to exercise more caution when evaluating policy outcomes. On the other hand, we employ the max share identification method to show that such heterogeneity also implies that different sectors may be subject to different shocks. While the current result could not pinpoint where these shocks originate, we can glimpse the different degrees of interconnectedness among different banking sectors and how they are linked to the economy.

Based on these results, there are several exciting directions we can take to further our understanding of this topic. Regarding the effect of monetary policy shock on banks, we stop our sample right before 2007 since the following crisis phase includes various structural changes in the banking sector and many unorthodox bail-out policies, which may render the SVAR analysis unreliable. However, the effect of unconventional monetary policy on banks and shadow banks is worth studying, as the zero lower bounds are still a constraint for many central banks worldwide even after the crisis. Therefore, the next step would be to evaluate the same question under the post-crisis regulatory framework and economic environment, which will test the effectiveness of the various reforms in the banking sector and a possible experiment for further policy intervention.

Several new experiments could be interesting for the identified shocks with the max share method. For instance, so far, we have not clearly defined the identified shock, nor do we know the relative importance of this shock to the other economic variables, such as housing market performance, consumption, or employment. The need for a clear definition of the shocks calls for experiments on the impulse responses of this shock. Besides, to what extent a shock generated outside of the banking sector can be amplified through banks and, eventually, evolves into a bubble large enough to trigger a systematic crisis is also worth further study of the transmission mechanism of the banking sector and the business cycle. As the banking system has become exceedingly diverse, the effectiveness of various policies and regulations will eventually hinge on how much we know about the defining features of different banks and how well we can pinpoint the key connects among these enormous and intricate players in the financial market.

1.6 Figures

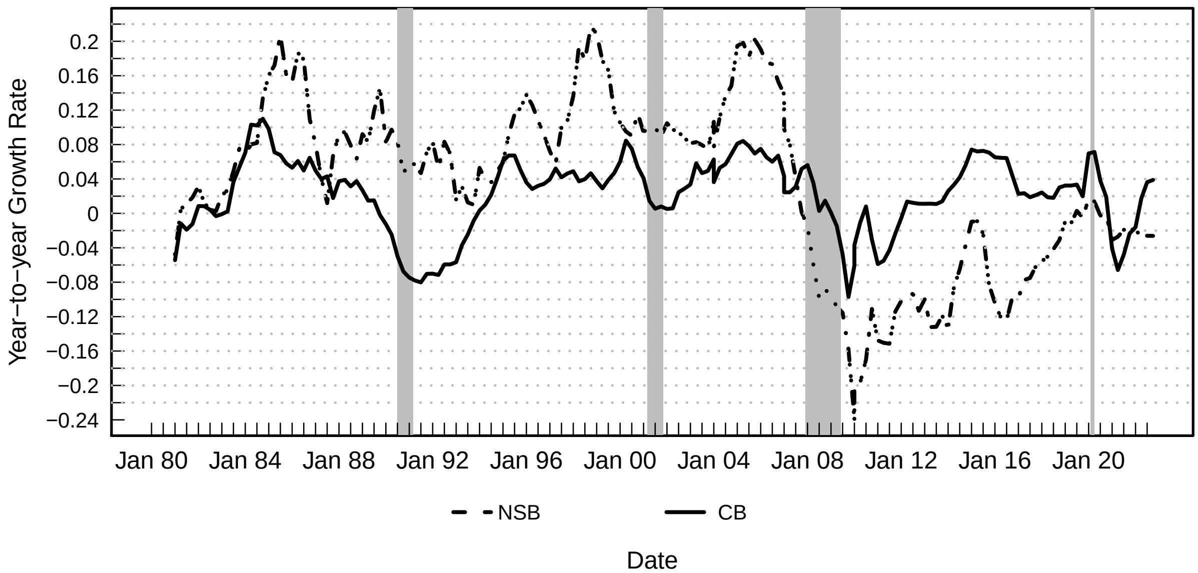

Figure 1.3: Loan Origination Growth Rate.

Notes: The plot shows the year-to-year growth rate of the loans originated by commercial and narrow shadow banks. Shaded regions denote the crisis periods.

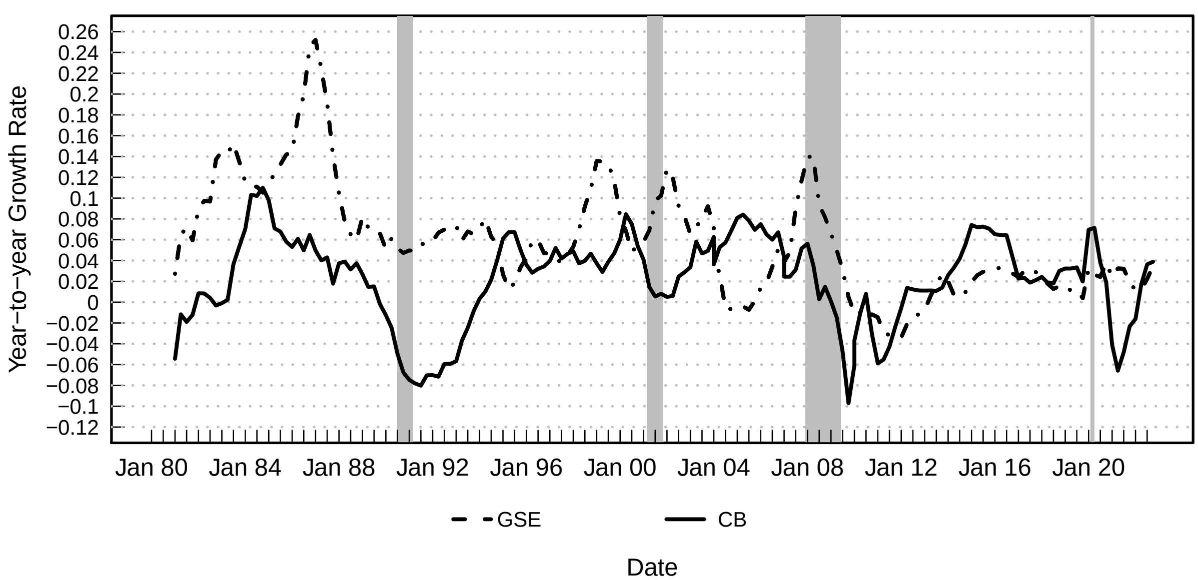

Figure 1.4: Loan Origination Growth Rate.

Notes: The plot shows the year-to-year growth rate of the loans originated by commercial and government-sponsored enterprises. Shaded regions denote the crisis periods.

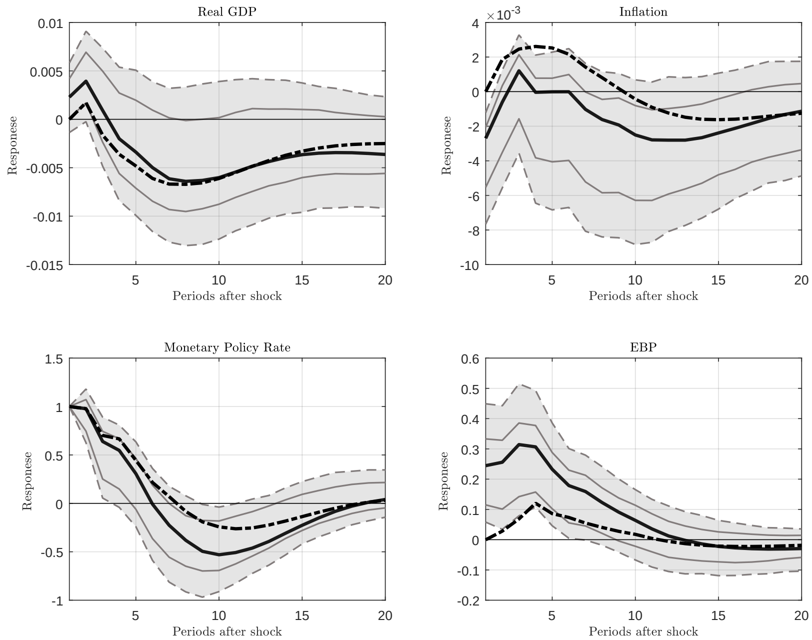

Figure 1.5: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the IRF of the monetary policy shock identified using proxy and short-run identification. The shaded area shows [16, 86] and [5, 95] percent confidence interval.

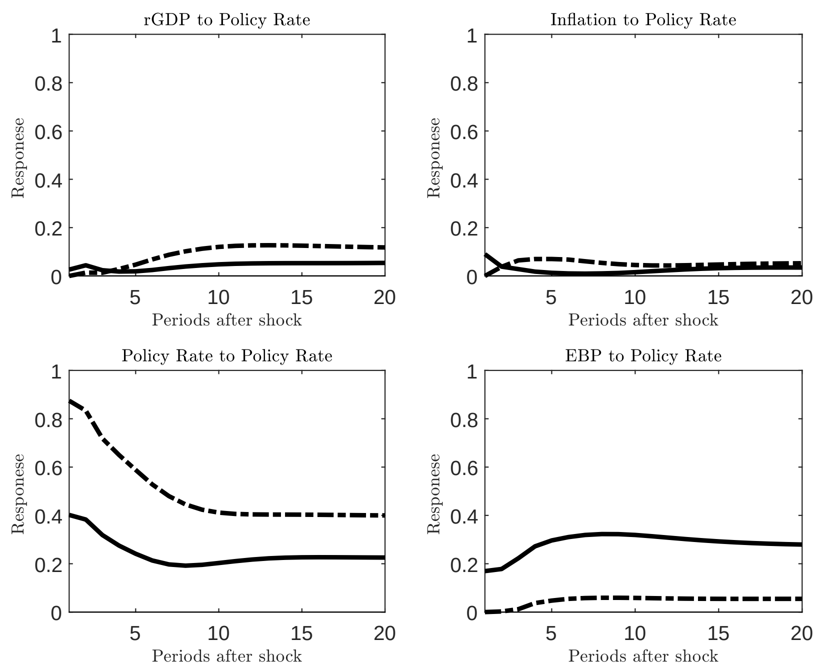

Figure 1.6: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the FEVD of the monetary policy shock identified using proxy and short-run identification.

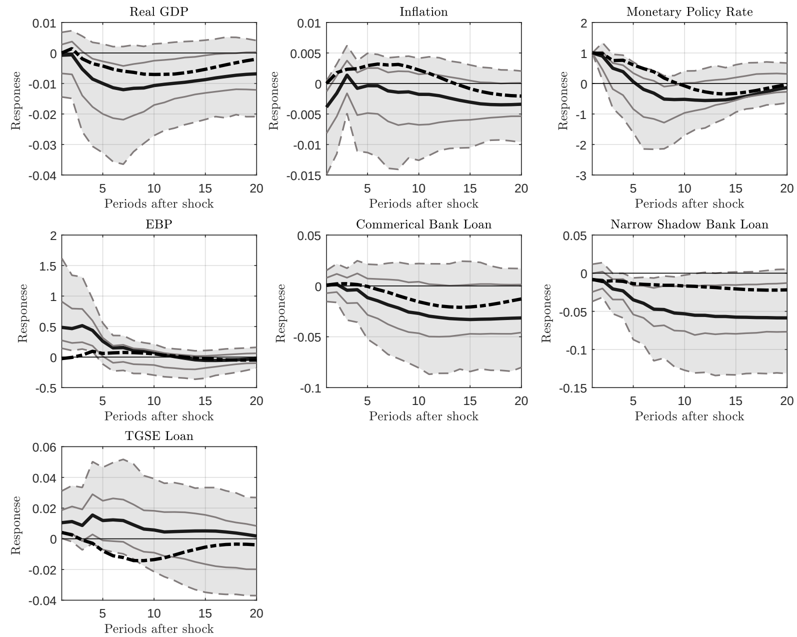

Figure 1.7: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the IRF of the monetary policy shock identified using proxy and short-run identification. The shaded area shows [16, 86] and [5, 95] percent confidence interval.

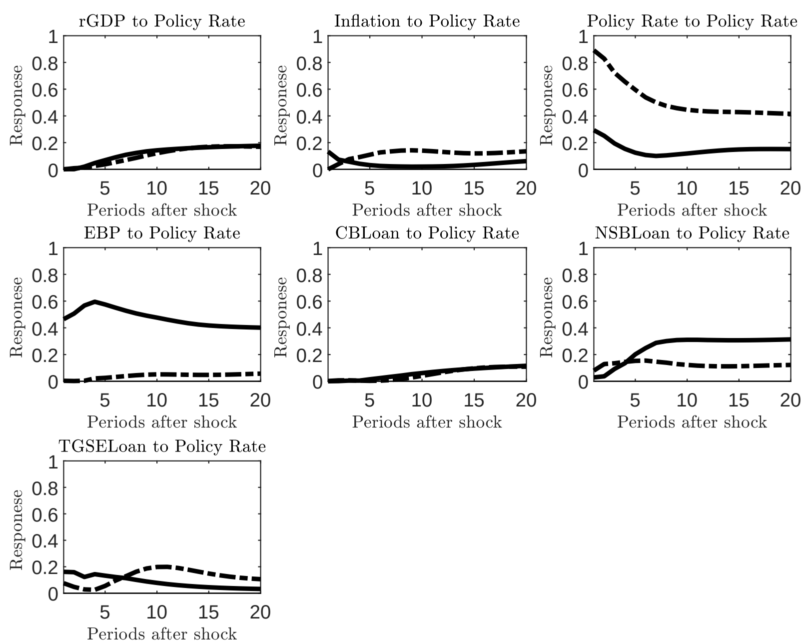

Figure 1.8: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the FEVD of the monetary policy shock identified using proxy and short-run identification.

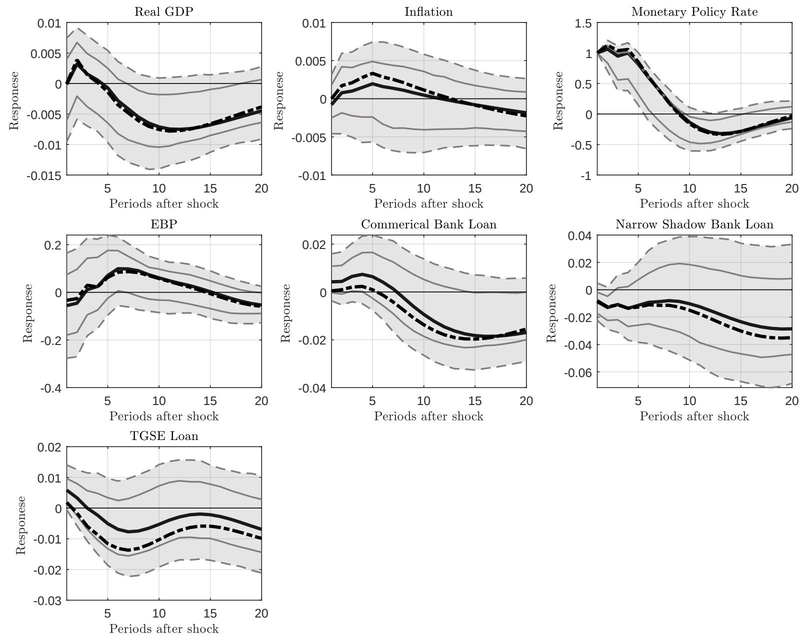

Figure 1.9: IRF of Monetary Shock (1980-2022).

Notes: The solid and dashed line show the IRF of the monetary policy shock identified using proxy and short-run identification. The shaded area shows [16, 86] and [5, 95] percent confidence interval.

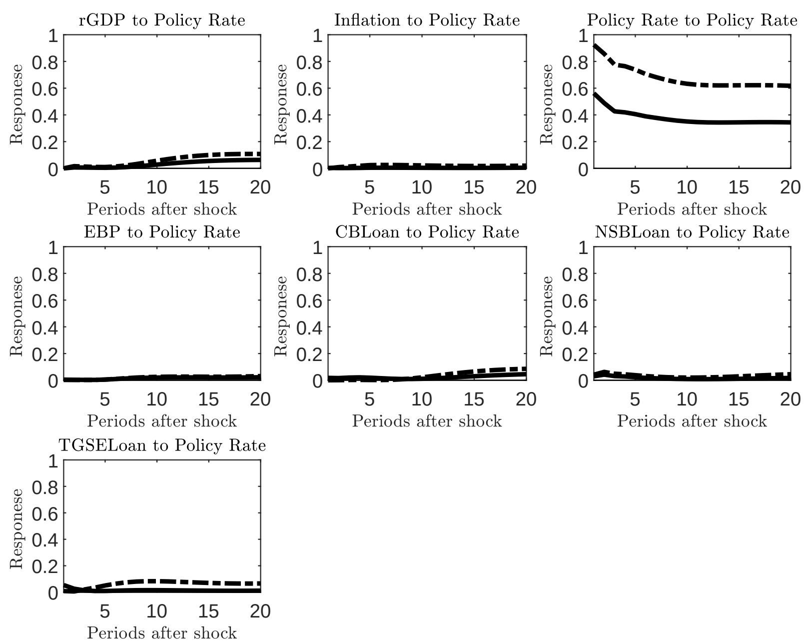

Figure 1.10: IRF of Monetary Shock (1980-2022).

Notes: The solid and dashed line show the FEVD of the monetary policy shock identified using proxy and short-run identification.

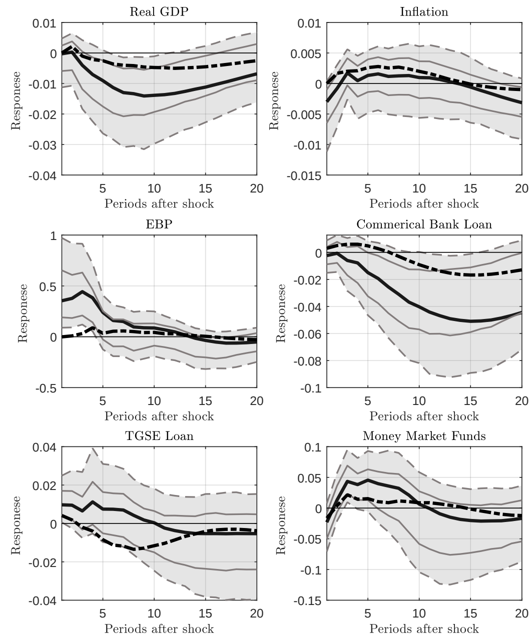

Figure 1.11: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the IRF of the monetary policy shock identified using proxy and short-run identification. The shaded area shows [16, 86] and [5, 95] percent confidence interval.

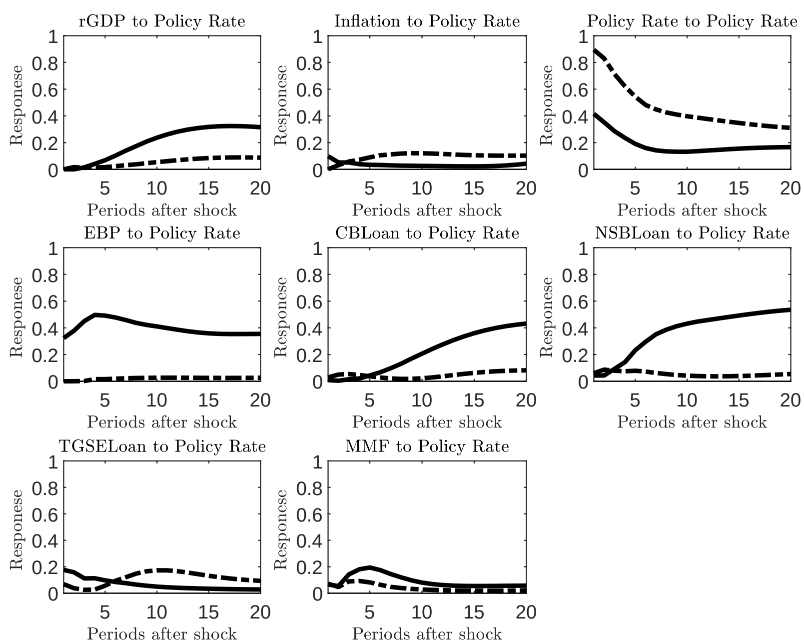

Figure 1.12: IRF of Monetary Shock (1980-2007).

Notes: The solid and dashed line show the FEVD of the monetary policy shock identified using proxy and short-run identification.

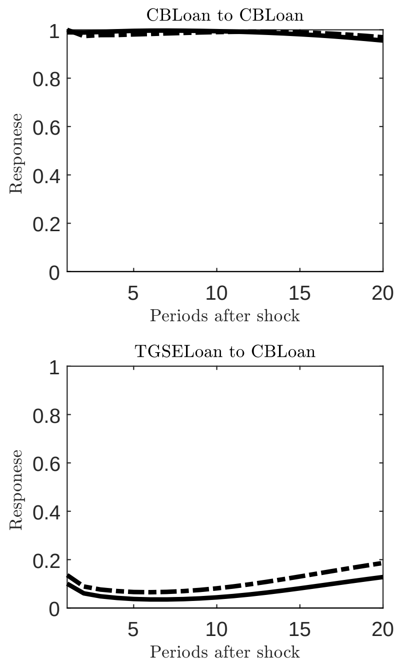

Figure 1.13: FEVD of CB Shock (1980-2007).

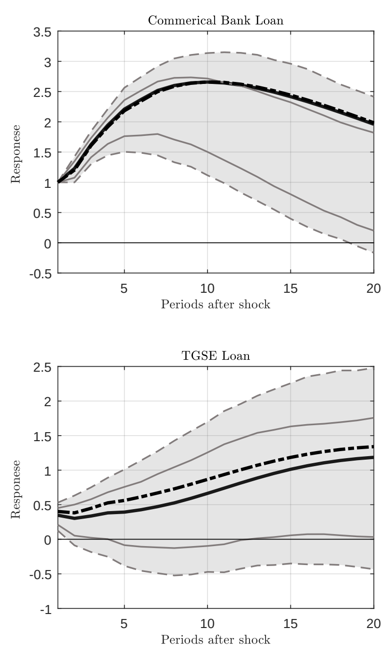

Figure 1.14: IRF to CB Shock (1980-2007).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of commercial bank loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

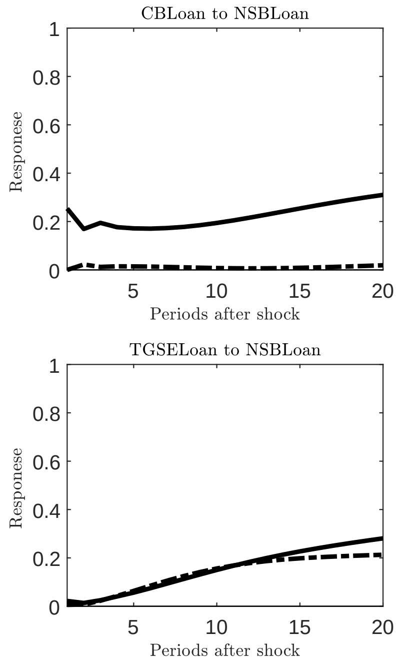

Figure 1.15: FEVD of NSB Shock (1980-2007).

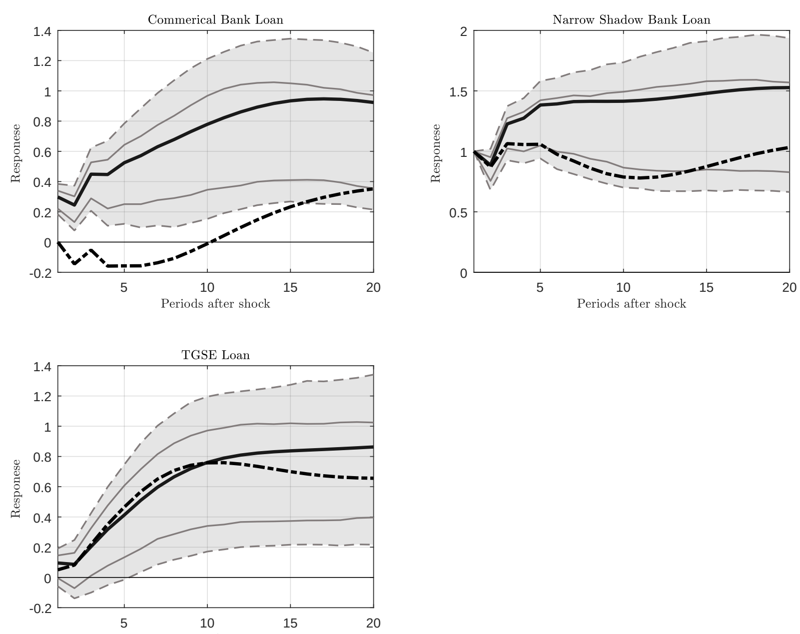

Figure 1.16: IRF to NSB Shock (1980-2007).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of narrow shadow bank loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

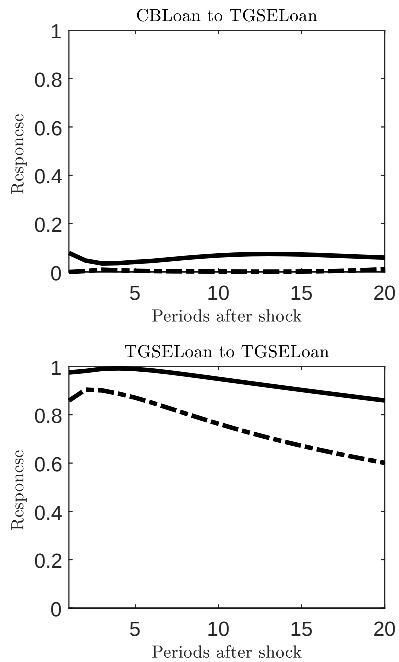

Figure 1.17: FEVD of GSE Shock (1980-2007).

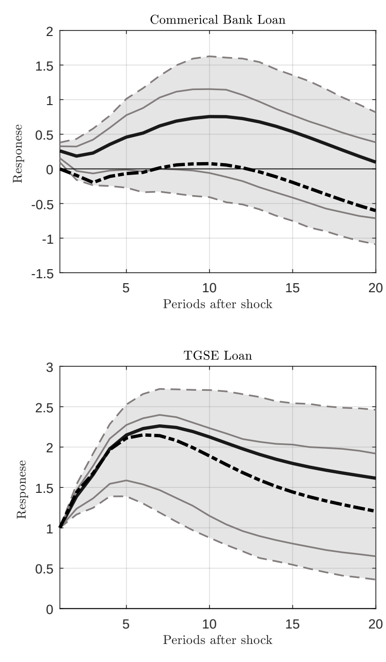

Figure 1.18: IRF to GSE Shock (1980-2007).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of narrow shadow bank loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

1.7 Appendix

1.7.1 Background

Bank vs. Market-based Credit Intermediation

Market-based financial intermediaries have been discussed in detail in Adrian and Shin (2010). Figure ?? is a simplified structure of the economy with the presence of these market-based financial intermediaries. As can be seen from the figure, the ultimate lenders in the economy are the households who choose to deposit their money directly in banks or put it in the money market. The money market consists of institutional investors like money market funds or pension funds, prominent investors in money market tools, and, thus, critical wholesale funding sources. In our study, we represent the money market with money market funds, for they are significant investors in short-term debts issued by shadow banks or backed by their securitization products. They have been fierce competitors of commercial banks in terms of deposit collection. The share of money market funds in the total deposit went up to approximately 40% in 2007, making MMFs a real competitor for banks.

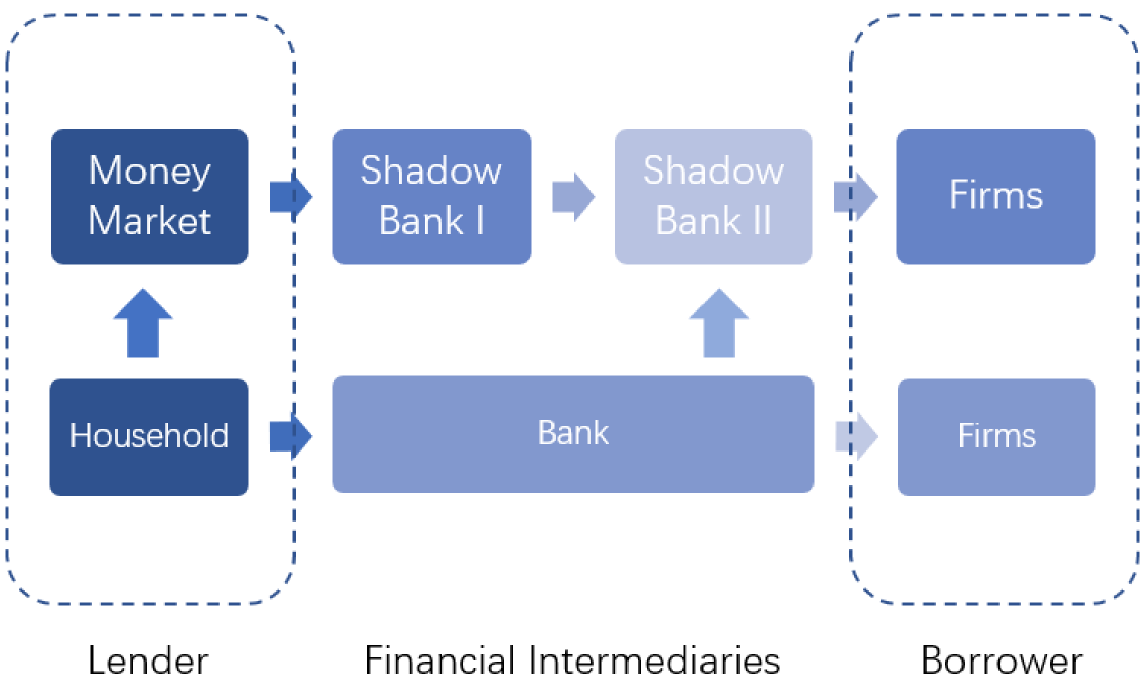

Figure 1.19: Financial Intermediaries in the Economy.

Financial intermediaries perform credit intermediation in the economy. Commercial (or traditional) banks dominated the playground until shadow banks began to catch up in the eighties. Among the institutions classified as shadow banks, there are several specialization categories. Gertler et al. (2016) classifies the shadow banking sector into origination, securitization, and funding institutions; each corresponds to a procedure in shadow banking activities. Shadow Bank II in Figure 1.19 corresponds to the origination and securitization of shadow banks, which generate loans and fund this holding by selling ABS to Type II shadow banks and commercial banks. Shadow Bank I funds the holding of ABS using money market instruments such as repurchase agreements and asset-backed commercial papers. The decomposition of the simplified balance sheet of these institutions can be found in Figure 1.20. The institutions in the shadow bank sector that we are interested in this paper can be seen as a synthesis of these different types of shadow banks, while in reality, not all shadow banks run this whole range of business. Most specialize in one of the two types of shadow banks discussed above.

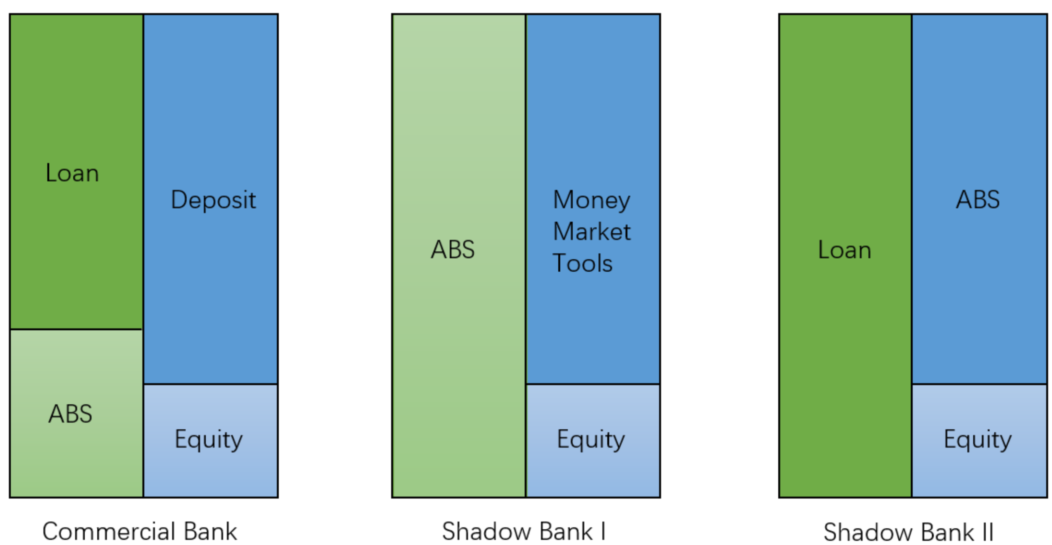

Figure 1.20: Balance Sheet Decomposition.

Note that this is a very simplified version of the economy's structure. Here we omit from discussing all the links between these institutions to have a clear illustration, of which the major ones are as follows. First, we leave out the shadow bank on the liability side of banks, i.e., an arrow pointing from shadow bank to commercial bank. While in reality, one crucial feature of shadow banks is to provide wholesale funding for banks, though it has never become the primary source of funding for banks. The share of deposits in total liability for banks hit the lowest point of 75% around 2008 and has been increasing steadily ever since. Second, the money market also provides short-term liquidity to corporations by issuing demand deposits, and around 18% of money market funds go back to banks. We leave out these arrows because it is the long-term finance of firms and banks that we mainly care about in this research.

Shadow Banking Sector

The definition of the shadow banking sector is surprisingly unclear and subject to different interpretations, as vastly different institutions are all umbrellaed under this term. Financial Stability Board (2016) defines shadow banks as follows: *Narrow measure of shadow banking includes non-bank financial entity types that authorities consider involved in credit intermediation where financial stability risks from shadow banking may occur.* Based on this definition and the previous illustration of the economic structure, we further formalize our object of interest through the following clarification.

First, we focus only on shadow banking in the loan market, thereby excluding money market participants (such as MMFs) from our definition of shadow banks. Although money market funds are sometimes referred to as deposit-side shadow banking, we view them as lenders providing wholesale funding. An alternative perspective would be seeing the money market and shadow bank together as a consolidated bank, representing the liability and asset side of these imaginary banks, respectively, since they each play the role of deposit creation and loan generation traditionally done by one bank. This is in line with the recent view calling for decoupling banks' dual role of deposit creation and loan generation. Nevertheless, we still exclude them from shadow banking because they are usually confined to the securities they can invest in and do not directly engage in loan generation.

Second, we restrict our attention to shadow banks that perform credit intermediation to the non-financial sector. As stated previously, shadow banks not only fund assets. These institutions are also important funding sources for banks and other financial institutions. An example of a shadow bank of this kind would be security brokers and dealers. Since our focus here is how financial intermediaries direct money to the non-financial sector, the shadow banks we discuss are the subset of the shadow banking sector that focuses on credit intermediation.

Third, shadow banking is not synonymous with securitization vehicles, as financial intermediaries generate loans without securitizing them. However, we restrict our attention to those closely related to this business. As stated previously, the shadow bank institutions we analyze combine the institutions that engage in various shadow banking activities: loan generation, securitization, and funding ABS through the money market.

To sum up, this paper's shadow banking of interest is the asset side of the shadow banking sector that focuses on credit intermediation with securitization. Table 1.1 shows how our definitions of shadow banks is linked with the corresponding measurements in the U.S. Financial Account dataset.

Table 1.1: Measurement of Shadow Banking in US Financial Account

Definition	Total Shadow Banking (Gertler *et al*. (2016))	
Narrow Shadow Banking	ABS Issuers (L.127) Finance companies (L.128) Funding Corporations (L.132)	Adrian & Shin (2011)
Total GSE	Government-sponsored enterprise (L.125) GSE mortgage pools (L.126)	Nelson *et al*. (2017)
Others	Security brokers & dealers (L.130) REITs (L.129) Holding Companies (L.131)	
Commercial Bank	Private depository institutions (L.110)	
MMF	Money Market Funds (L.121)	

Connection between Commercial and Shadow Banks

Commercial and shadow banks can become correlated through two channels. First is the direct holding of ABS, which is observable from banks' balance sheets. The second one is that banks provide implicit guarantees to shadow banks when shadow banks finance long-term assets. This, of course, cannot be captured by balance sheet variables and needs to be noticed.

Direct holding of ABS is closely related to one core feature of shadow banks that we want to capture here: conduct loan securitization to supply a large amount of information-insensitive, highly-rated liquid assets (asset-backed securities) that qualify as collateral against borrowing. The reason for holding such assets could also be strategic, namely, performing regulatory arbitrage. Efing (2016) finds that banks take advantage of the fact that the capital requirement for ABS holdings is less risk-sensitive. Therefore banks that are more constrained in the capital would intentionally pursue ABS with the highest yield among all the ABS with the same risk weights.

In addition to direct asset holding, more implicit connections are built when shadow banks obtain guarantees for their liabilities from commercial banks. Studies such as Acharya et al. (2013) have shown that banks use this type of implicit guarantee to circumvent regulations and take on more credit risks. These, of course, influence the asset side of the bank's balance sheet. On the liability side, money market funds that profit from money market tools also compete against banks for retail deposits and, in turn, direct more money toward the shadow banking sector. These interdependent relationships make the financial intermediaries sector opaque and complex, and such opaqueness can have severe consequences once the potential risk of the safe asset unravels.

1.7.2 Stylized Facts

Trend

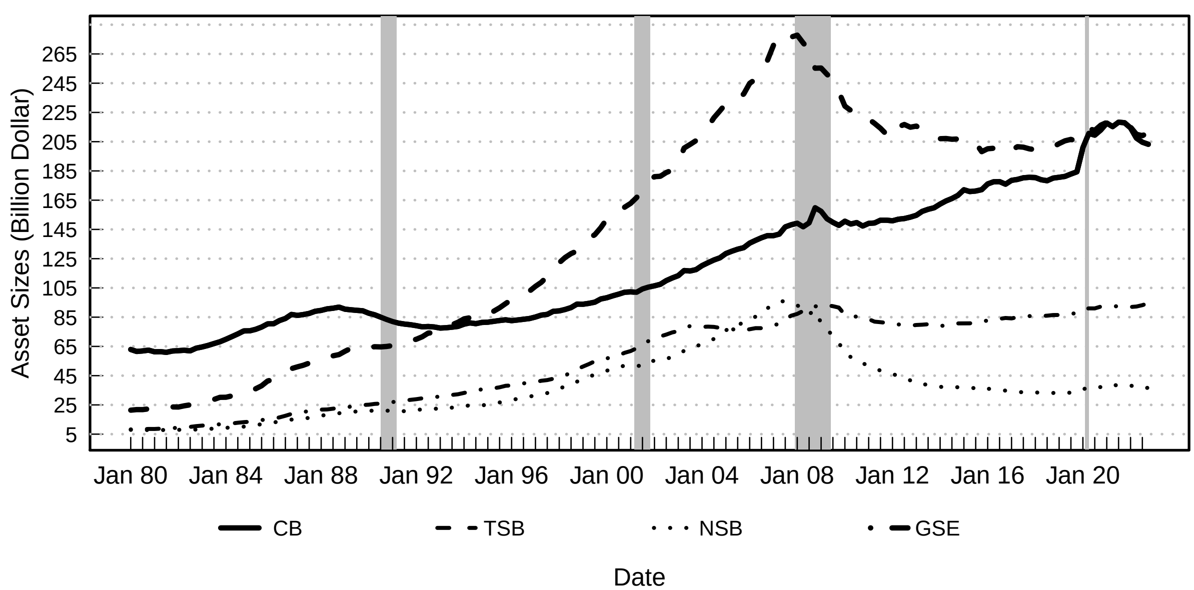

Figure 1.21: Total Asset.

Notes: The plot shows total asset quantities of four groups of banks, commercial banks, narrow shadow banks, government-sponsored enterprises, and total shadow banks. Details on the classification of the banks can be found in Appendix **??**. The loan quantity is in real terms (deflated using core CPI). Shaded regions denote the crisis periods.

Commercial Banks

To get a glimpse of whether commercial and shadow banking has become more integrated over the years, we examine the commercial banks' balance sheet. Figure 1.22 shows the decomposition of the total asset of commercial banks. We can see that loans and debt security constitute the majority part of the banks' total asset. Within the debt securities category, however, things are quite different, as shown in Figure 8. The share of Agency and GSE-backed securities in all the debt securities has been on the rise steadily and reached almost one half in 2017, while the share of treasury and municipal securities has been shrinking. This indicates that commercial banks may indeed use shadow banking products as a substitute for the liquid asset, or pseudo safe asset. Banks and shadow banks has thus become inevitably more intertwined over the course of time.

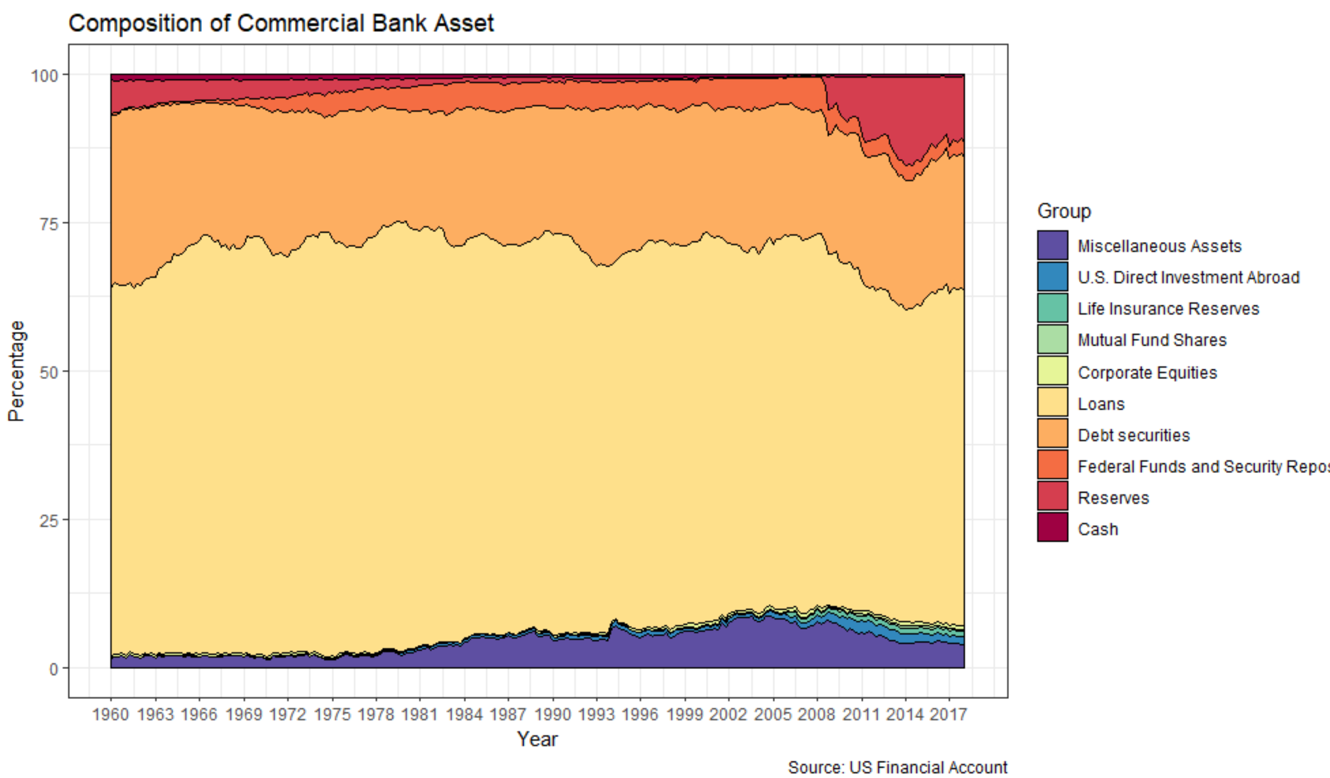

Figure 1.22: Decomposition of Bank Asset

Figure 1.23 shows the decomposition of the debt security holdings of commercial banks.

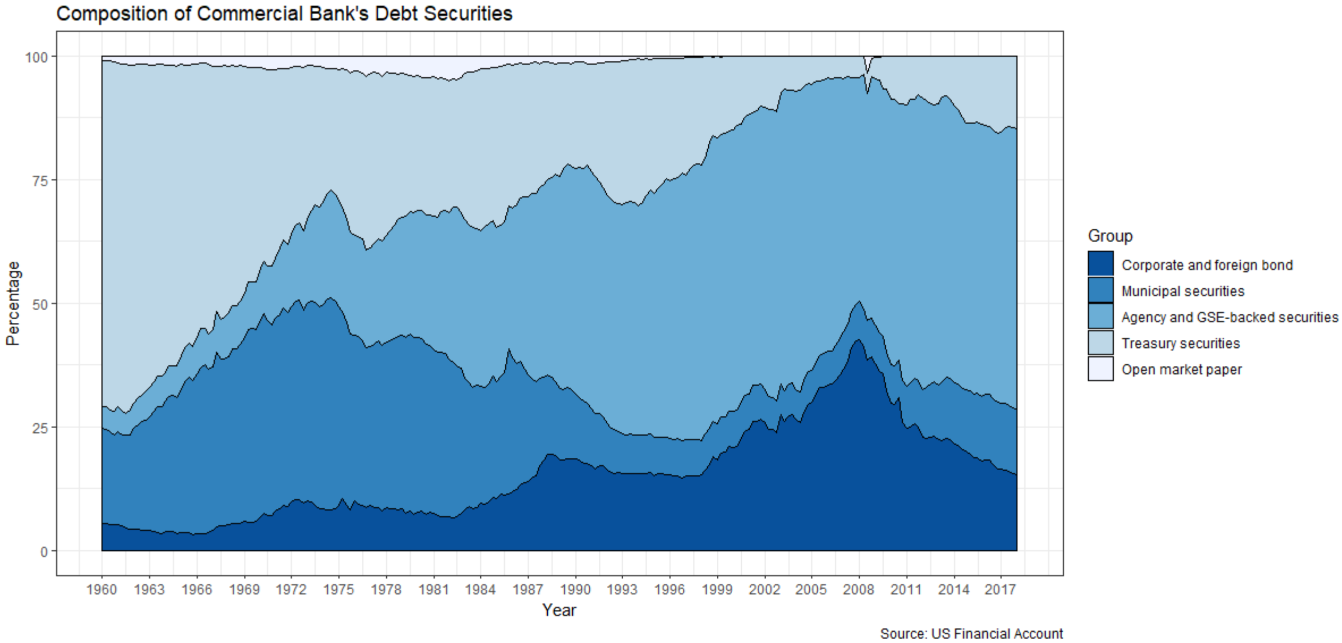

Figure 1.23: Decomposition of Debt Securities

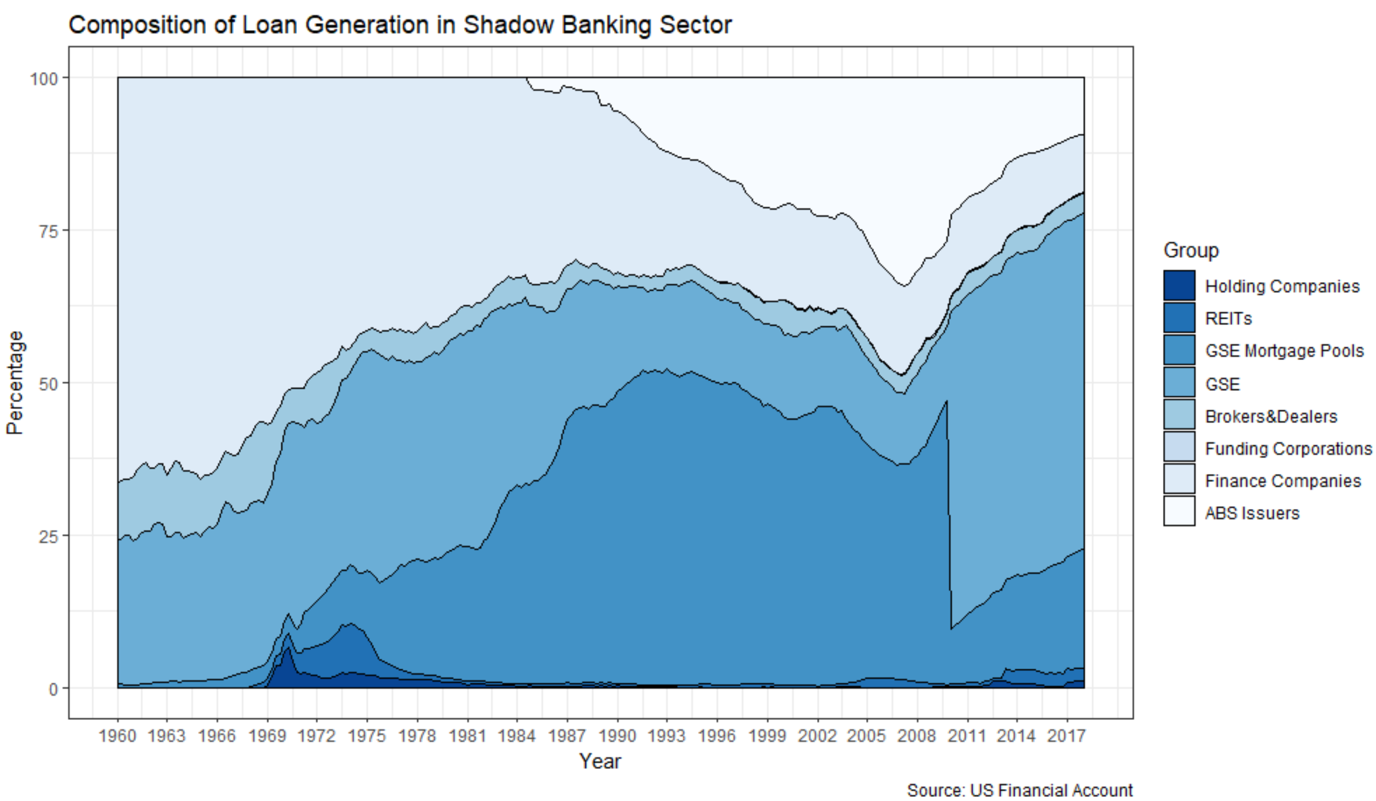

Figure 1.24: Loan Generation in Shadow Banking Sector

Shadow Banks

Figure 1.21 shows how market-based credit intermediaries have been developing quickly until the recent setback during the financial crisis. We can see that commercial bank asset (red line) was surpassed by total shadow bank asset (blue line) in the 1990s. Individually, our measure of Narrow Shadow Banking and Total GSE are of similar size and trend until the crisis hit, with former beginning to drop and the latter managing to sustain their pre-crisis level. This indicates that the level of total shadow bank ceased dropping mainly due to Total GSE. The trend for loans (Figure 6) is similar to the total asset. We can see that Total Shadow bank loans exceeded commercial banks around the same time as in the case of total asset. However, commercial bank loans exhibit strong growth in recent years and almost catches up with shadow loans level in 2017.

1.7.3 SVAR Analysis

Variable Description

Table 1.2: Data Description

Variable	Data	Data Description
Output	GDPC1(ln)	Real Gross Domestic Product
	GDPC1 (FD)	RGDP first difference
Inflation	CPIAUCSL (ln)	Consumer Price Index for All Urban Consumers
	PCECTPI (ln)	Personal Consumption Expenditures
Monetary Policy	FEDFUNDS	Effective Federal Funds Rate
	DGS1	1-Year Treasury Constant Maturity Rate
	DGS2	2-Year Treasury Constant Maturity Rate
	Shadow Rate	Shadow interest rate by Wu and Xia (2016)
Financial Intermediaries	Cbankrvalue (ln)	Private depository institutions real total asset
	TGSErvalue (ln)	GSE and GSE mortgage pools real total asset
	NSBrvalue (ln)	Narrow shadow banks real total asset
	Cbankrloan (ln)	Private depository institutions real total loans
	TGSErloan (ln)	GSE and GSE mortgage pools real total loans
	NSBrloan (ln)	Narrow shadow banks real total loans
Risk Indicator	EBP	Excess bond premium by Gilchrist and Zakrajšek (2012)

Monetary Policy Shock

Proxies for Monetary Policy Shocks.

The data for the monetary policy shock proxies comes from the following papers: Gürkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), and Acosta (2022).

Table 1.3: Proxy Variable Description

Paper	Data	Description
Gürkaynak et al. (2005)	mp1_tc	Surprises in the current month fed funds futures
	ff4_tc	Surprises in the three month ahead monthly fed funds futures
	ed2_tc, ed3_tc, ed4_tc	Surprises in the six month, nine month and year ahead futures on three month Eurodollar deposits
Nakamura and Steinsson (2018)	news shocks	policy news shocks
	FFR shock	
Acosta (2022)	ns	Nakamura and Steinsson (2018) policy news shock
	ff.shock.0	30-minute change in expectations of the Federal Funds rate immediately after each FOMC meeting (the first component of the policy news shock)

Proof of Proxy Identification.

Given the reduced-form errors $\mathbf{u}_t$, define u_t^p be the reduced form residual for the monetary policy indicator, and $\mathbf{u}_t^q$ that of the other variables estimated. From the assumptions in Equation 1.3.2, we perform the following two-step estimation procedure that help us identify the structural monetary policy shock.

Step I To isolate the impact of the shock of interest, ϵ_t^p, we regress u_t^p on Z_t. Since Z_t is orthogonal to all structural shocks but u_t^p, the fitted value $\hat{u}_t^p$ contains only the information from the monetary policy shock.

$$u_t^p = \phi_0 + \phi_1 Z_t + \zeta_t$$

Step II Regress the other reduced-form residuals on the fitted value from the first step, $\hat{u}_t^p$.

$$\boldsymbol{u}_t^q = \psi_0 + \boldsymbol{\psi}_1 \hat{u}_t^p + \xi_t \tag{1.7.1}$$

The equation can be estimated without bias since the exogeneity condition of the variable Z_t guarantees that $\hat{u}_t^p$ is orthogonal to the error term ξ_t. The intuition of the 2SLS estimation is that the entries in $\boldsymbol{u}_t$ are correlated, as they are the results of a linear combination of different structural shocks. Therefore, it is sufficient to compare the projections of these variables on the exogenous instrument to isolate the effect of one structural shock on the endogenous variable.

Step III Consider partitioning the vector of reduced form residuals as $\mathbf{u}_t = \left[u_t^p \mathbf{u}_t^{q'}\right]' = [u_{1t}\mathbf{u}_{2t}']'$, and the corresponding matrix of structural coefficients as

$$\mathbf{S} = \begin{bmatrix} \mathbf{s} & \mathbf{S}_q \end{bmatrix} = \begin{bmatrix} \mathbf{S}_1 & \mathbf{S}_2 \end{bmatrix} = \begin{bmatrix} s_{11} & \mathbf{S}_{12} \\ \mathbf{S}_{21} & \mathbf{S}_{22} \end{bmatrix}$$

and the reduced form variance-covariance matrix as

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

s^p is identified up to a sign convention and can be obtained by the following closed form solution

$$(s^p)^2 = s_{11}^2 = \Sigma_{11} - \mathbf{s}_{12}\mathbf{s}_{12}'$$

where

$$\mathbf{s}_{12}\mathbf{S}_{12}' = \left(\Sigma_{21} - \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{11}\right)' \mathbf{Q}^{-1} \left(\Sigma_{21} - \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{11}\right)$$

with

$$\mathbf{Q} = \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{11}\frac{\mathbf{s}_{21}'}{s_{11}} - \left(\Sigma_{21}\frac{\mathbf{s}_{21}'}{s_{11}} + \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{21}'\right) + \Sigma_{22}$$

The derivation is the straightforward application of the restrictions in 10 noticing that

$$\left(\Sigma_{21} - \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{11}\right)' \left(\Sigma_{21} - \frac{\mathbf{s}_{21}}{s_{11}}\Sigma_{11}\right) = \mathbf{s}_{12}\mathbf{Q}\mathbf{s}_{12}'$$

Sector-specific Analysis

Sample Period Robustness Checks.

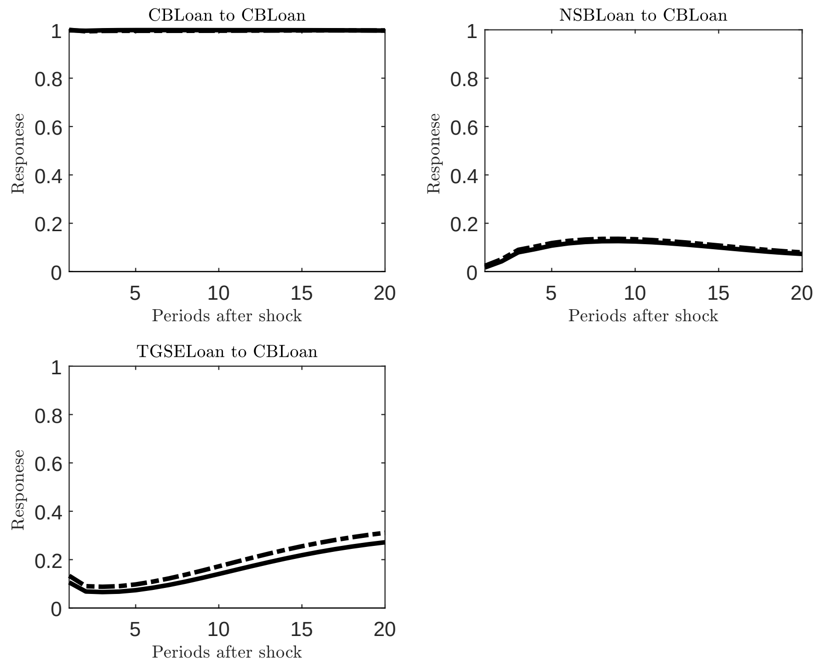

Figure 1.25: FEVD of CB Shock (1980-2022).

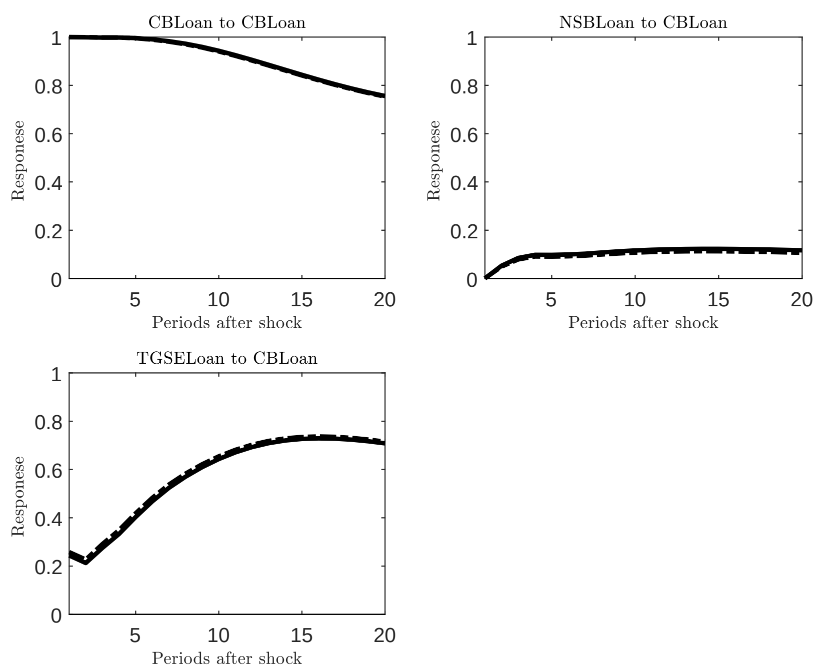

Figure 1.26: FEVD of CB Shock (2007-2022).

Notes: The solid line shows the FEVD of the shock identified using the max share approach to explain the forecast error variances of commercial bank loans. The dashed line shows the FEVD using short-run identification with the three variables in the current order.

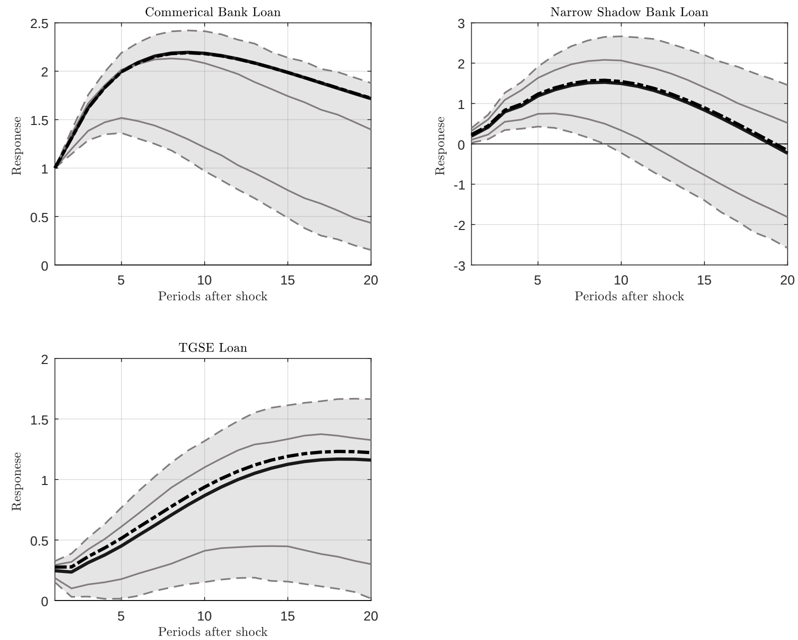

Figure 1.27: IRF to CB Shock (1980-2022).

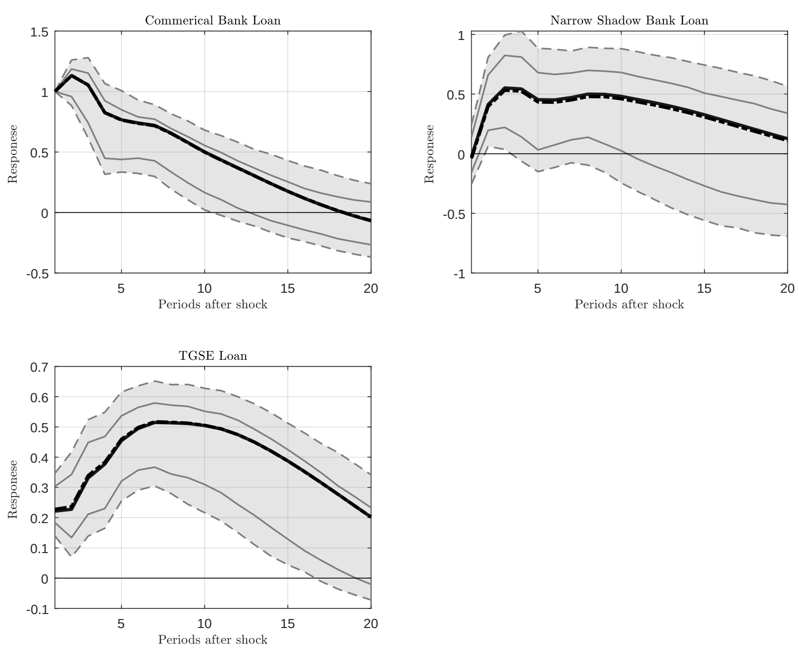

Figure 1.28: IRF to CB Shock (2007-2022).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of commercial bank loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

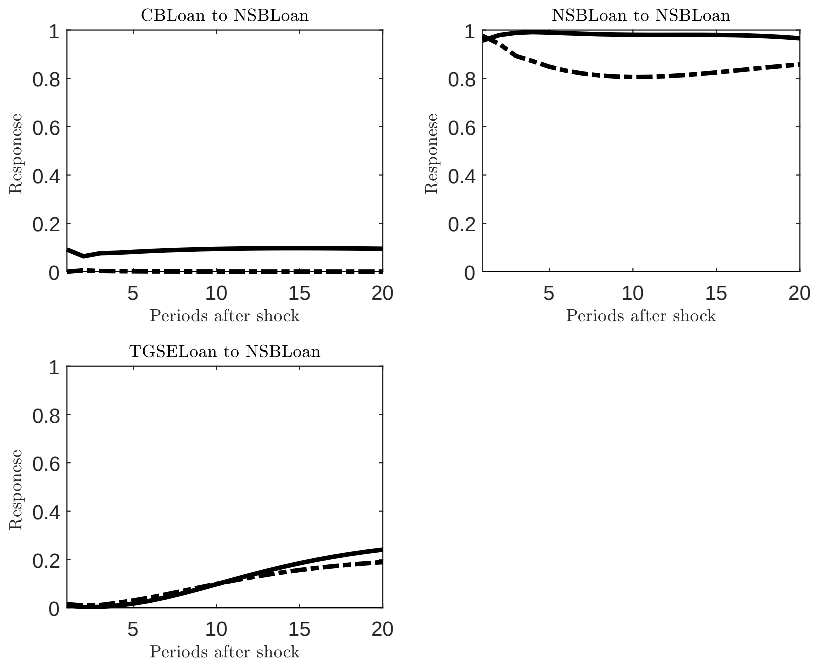

Figure 1.29: FEVD of NSB Shock (1980-2022).

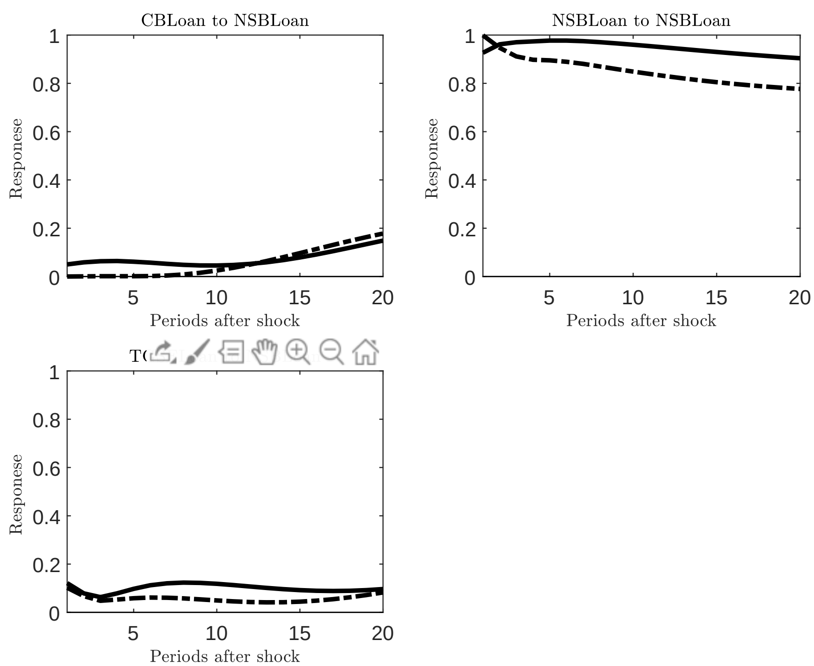

Figure 1.30: FEVD of NSB Shock (2007-2022).

Notes: The solid line shows the FEVD of the shock identified using the max share approach to explain the forecast error variances of narrow shadow bank loans. The dashed line shows the FEVD using short-run identification with the three variables in the current order.

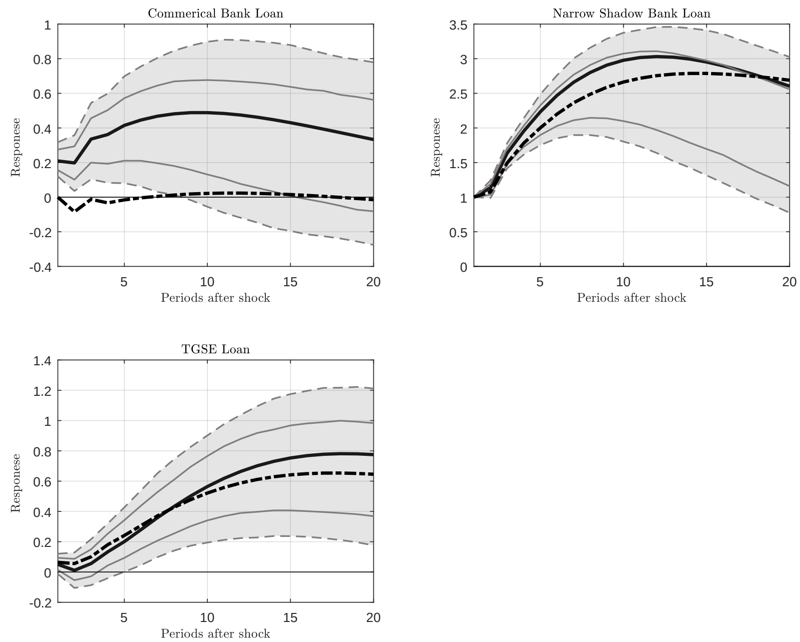

Figure 1.31: IRF to NSB Shock (1980-2022).

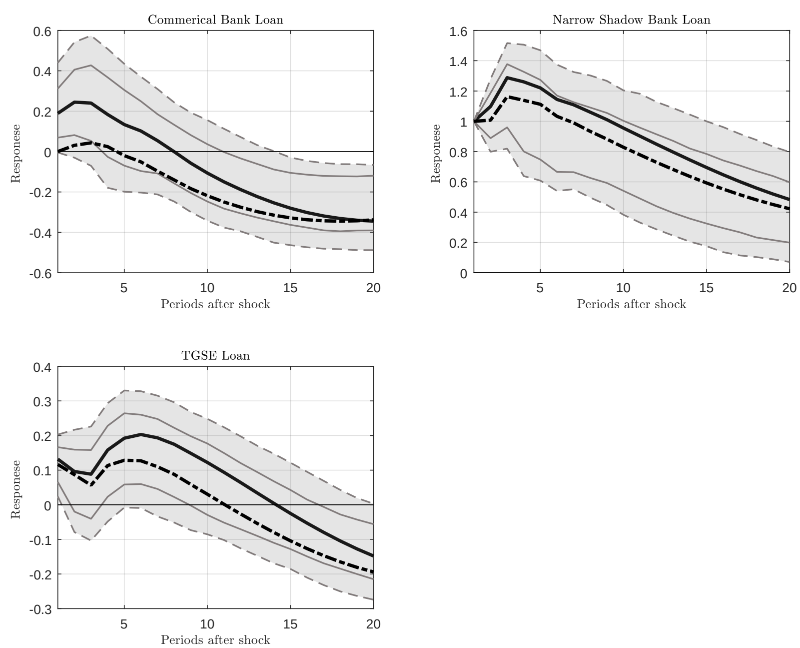

Figure 1.32: IRF to NSB Shock (2007-2022).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of narrow shadow bank loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

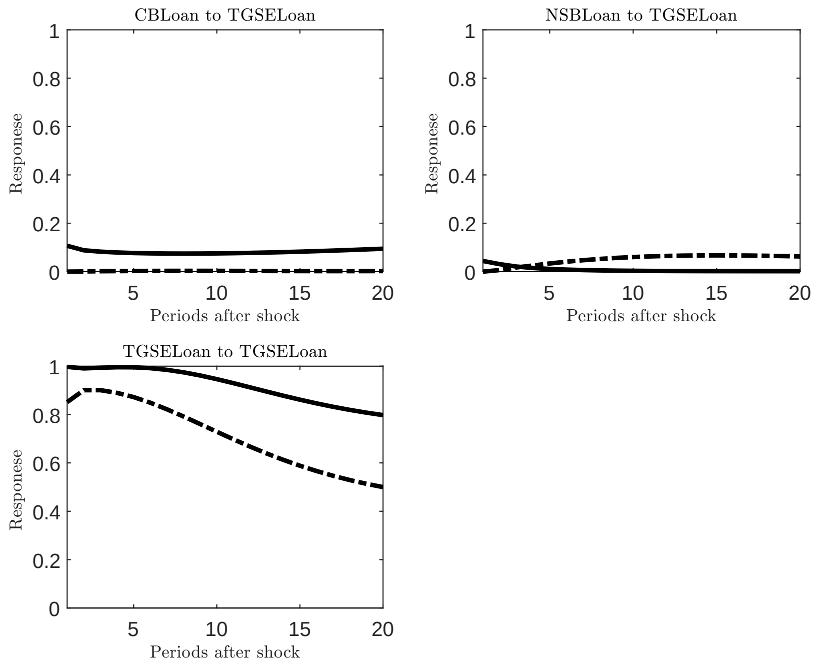

Figure 1.33: IRF to GSE Shock (1980-2022).

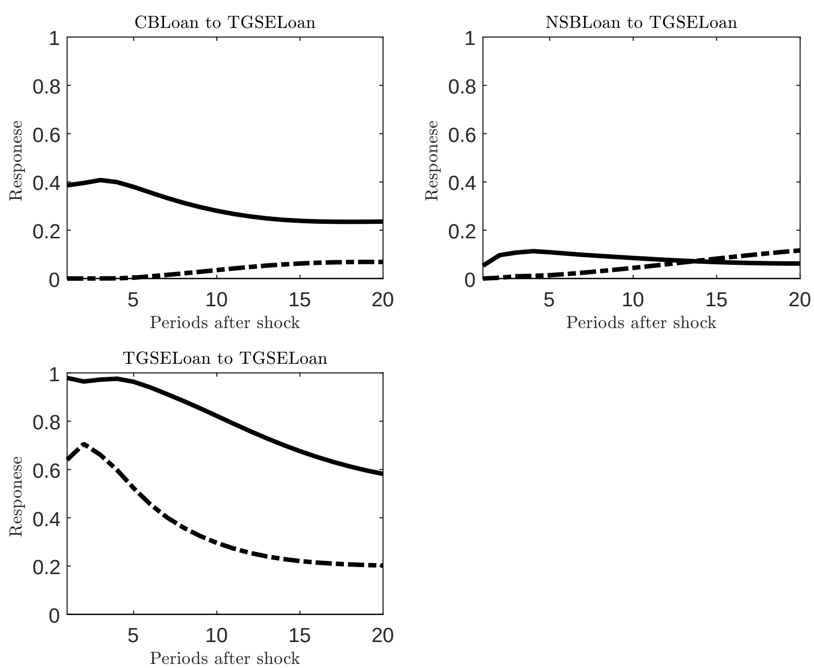

Figure 1.34: IRF to GSE Shock (2007-2022).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of GSE loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

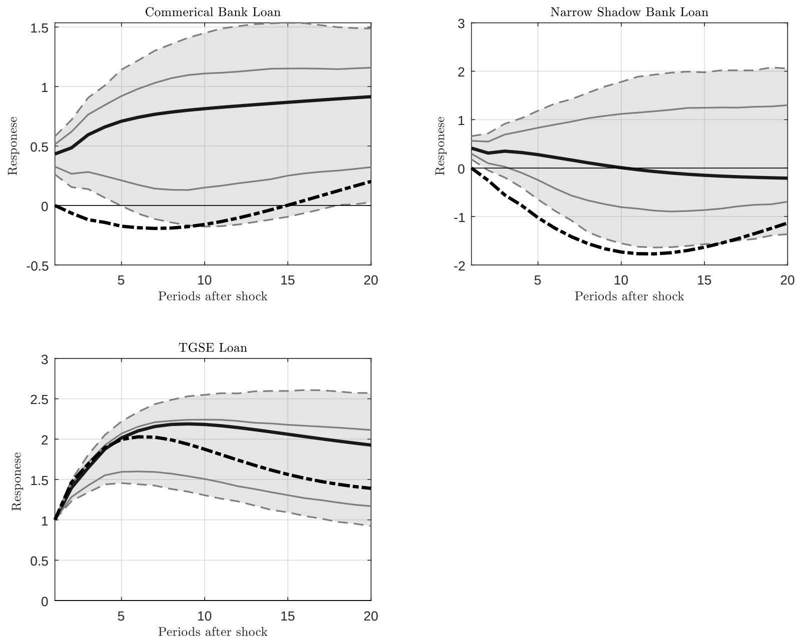

Figure 1.35: IRF to GSE Shock (1980-2022).

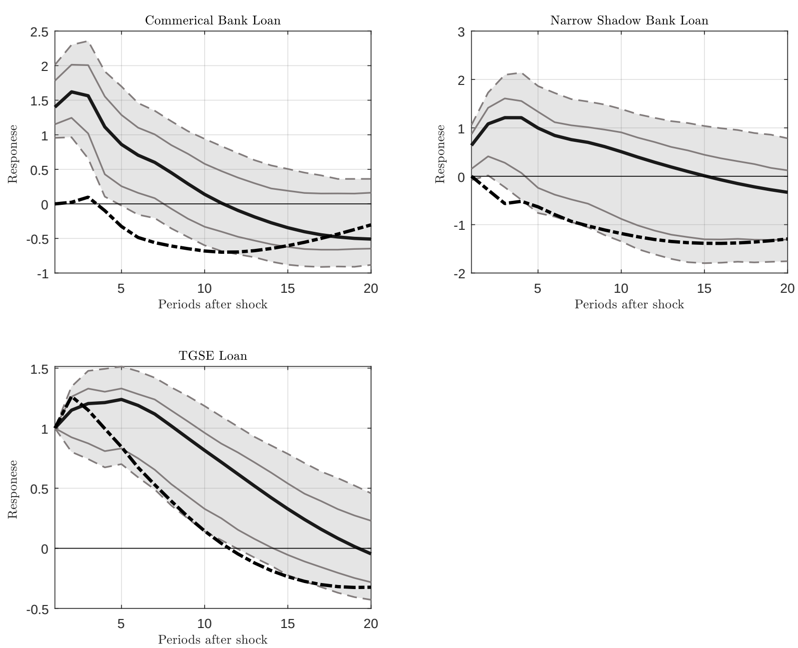

Figure 1.36: IRF to GSE Shock (2007-2022).

Notes: The solid line shows the impulse responses to the shock identified using the max share approach to explain the forecast error variances of GSE loans. The dashed line shows the IRF using short-run identification with the three variables in the current order.

Chapter 2

Monetary Policy and Global Bank Lending: A Reversal Interest Rate Approach

Li Yu and Philipp Wangner[1]

...the banker must not only know what the transaction is which he is asked to finance and how it is likely to turn out but he must also know the customer, his business and even his private habits, and get, by frequently "talking things over with him", a clear picture of the situation.

Joseph A. Schumpeter (1939)

2.1 Introduction

Monetary policy affects the economy via a *credit channel*, i.e., bank lending responds to policy rate changes, which in turn affects the prices and output in the economy. Research on this channel often focuses on the *quantity* of bank lending. However, in an open economy environment, globally operating banks (hereafter global banks) simultaneously decide the lending *quantity* and the *composition* of domestic and foreign lending. It is unclear whether these two types of lending respond to monetary policy similarly and, if not, which mechanisms contribute to the geographical portfolio re-balancing. Understanding this question is of crucial

[1] A previous version was entitled *Bank Home Bias and Monetary Policy*. We are extremely grateful to Patrick Fève, Fabrice Collard, Christian Hellwig, and Nicolas Werquin for their invaluable advice and continuous support. We also thank all the participants at the EEA 2022 in Milano, the YES Conference 2022 in New Haven, the International Conference on US China Trade Disputes and Rearchitecture in Globalization 2022 in Beijing, and the TSE Macro and Finance workshop for constructive comments and insightful discussions. All remaining errors are our own.

importance to the evaluation of the effectiveness of the monetary policy. If banks respond to policy rate changes by substituting domestic lending with foreign lending, policy impact on the domestic economy is compromised. Moreover, portfolio re-balancing following rate adjustments raises concerns for financial stability, as this implies that monetary policy alters banking sectors' international risk exposure.

This paper studies the impact of monetary policy on the credit allocation of global banks. We develop an analytical framework for global bank lending. In the framework, banks allocate their lending to both domestic and foreign borrowers for diversification benefits, but foreign lending comprises higher uncertainty due to cross-border frictions. Managing the uncertainty is costly and depends on banks' profitability driven by margins between lending and deposit rates. As a result, the effect of expansionary monetary policy on bank lending allocation is state-dependent. In times of low interest rates and large balance sheets, a further cut in the interest rate decreases bank profitability and has opposite effects on domestic and foreign lending. Our model thus sheds new light on the concept of the *reversal interest rate* (Brunnermeier and Koby, 2018; Darracq Pariès et al., 2020), which refers to a level of interest rate below which a further cut in policy rate suppresses bank lending. Given that the effect of an interest rate cut on profitability matters more for foreign lending than domestic lending, the reversal rate in the closed economy becomes a *reversal rate corridor* in the open economy, within which a rate cut boosts domestic but suppresses foreign lending.

The core setup of the analytical framework is a global bank model in a two-country open economy. In the model, each country has a representative banking sector. The banks collect local deposits but invest in both domestic and foreign loans, which are risky. In addition, the banks can invest in a risk-free asset whose return is determined by the monetary policy rate. Banks are risk-averse and thus consider both the first and second-order moments of the risky loan returns when deciding their portfolio composition. In addition, the model features an imperfect pass-through of the policy rate to the deposit and lending rates. Thus, the monetary policy rate affects banks' profitability by altering the net interest margin. To see how monetary policy affects bank profits, we decompose profits into three components: Risk premium from domestic loans, risk premium from foreign loans, and risk-free profits arising from the difference between risk-free earnings on the assets and deposit repayment. The monetary policy rate plays a role in all three components. As a result, our model captures two channels of monetary policy transmission: the risk-premium channel and the profitability channel.

Notably, our model features an *uncertainty management* mechanism; that is, we assume that the variance of the investment return is *endogenous*, in the sense that it can be reduced by costly management. Such management activities have long been studied in the corporate finance literature, particularly when both investment possibilities and risk management encounter financial frictions (Froot et al., 1993; Rampini and Viswanathan, 2010; Bolton et al., 2011, 2013). For financial institutions, risk management considerations may conflict with investment decisions since they have a substantial proportion of non-tradable assets with a highly opaque quality in their portfolios (Froot and Stein, 1998). The fact that such management activity is costly highlights the importance of banks' profitability. In line with the recent empirical evidence (Ellul and Yerramilli, 2013), we assume that bank profits decrease the cost of managing in the baseline analytical model [2]. This relationship brings about two additional complications. First, the decision on the asset side of banks' balance sheets, i.e., their portfolio allocation, is no longer independent of their liability structure because the liability structure affects profitability. Second, similar to the Froot and Stein (1998), the investment decisions in the different assets are not independent. In our model, this dependence arises because profits from one investment can affect the management cost of the other.

The model has the following implications. Regarding gross lending quantity, cross-border uncertainty friction unambiguously biases banks' foreign investment downward. In contrast, the impact on domestic investment depends on the degree of complementarity of domestic and foreign assets, which depends on the correlation between the fundamentals of the two countries. Regarding monetary policy transmission, the effect is determined by multiple channels. On the one hand, when the uncertainty due to cross-border lending is exogenous, monetary policy influences portfolio allocation exclusively through the risk premium channel. If, on the other hand, uncertainty is determined endogenously through costly management, the impact of monetary policy on bank profitability becomes crucial for portfolio allocation, as bank profits alter the cost of management that banks pay. Profit declines after policy rate cuts always have a more substantial negative impact on overseas lending because of the comparative advantage in managing domestic uncertainties. Consequently, the effect of an interest

[2]Since our goal is to provide a positive analysis of the consequences of uncertainty management on bank lending, we omit a strict micro-foundation for this assumption in the model. Nevertheless, the relationship between profitability and risk management can be attributed to two mechanisms, which we plan to elaborate on in a separate paper. The first mechanism is raising external financing involves additional cost (Froot and Stein, 1998); therefore, higher profits help banks build up their capital and thus effectively lower the cost. The second mechanism is the collateral constraint and revenues as the collateral mechanism (Rampini and Viswanathan, 2010, 2013) Brunnermeier and Koby (2018) assumes a capital constraint that works similarly to collateral. As high profits imply better collateral values, it lowers the borrowing cost. The degree to which higher profits help decrease the cost thus reflects the shadow price of the collateral constraint.

rate cut on a bank's lending allocation is state-dependent, depending on the relative strength of the risk premium channel and profitability channel. When the asset size is large or the pass-through elasticity is low, the model shows that an expansionary monetary policy might have the unexpected consequence of boosting bank home bias.

Our model provides new insights into monetary policy transmission and effectiveness. For the credit channel of monetary policy, we demonstrate that in an open economy, monetary policy adjustments have a composition effect on banks' lending, tilting the balance between domestic and foreign investment. This effect arises from the profitability channel, because bank profits affect their lending decisions. This effect is asymmetric for domestic and foreign assets due to additional uncertainty for foreign investment. In addition, our analysis contributes to the recent discussion on the reversal rate. In our model, a policy rate cut can have opposite effects on domestic and foreign lending. This indicates that the reversal rate for domestic lending might be a lower bound in an open economy. That is, the effect of a policy rate cut on foreign lending can already be negative before the negative impact on domestic lending emerges. If this heterogeneity in the responses from banks' domestic and foreign lending is overlooked, the overall effect of a policy rate change on the domestic economy can be over or under-estimated, depending on whether the re-balancing between domestic and foreign lending attenuates or amplifies the policy impact on the domestic economy.

To evaluate this macroeconomic consequences and illustrate the impact of a sequence of policy rate changes, we extend the static bank model into a dynamic bank problem. Then we embed the model into a full-blown macroeconomic model with nominal rigidity. The dynamic bank model is an incomplete market model in an open economy setup. Banks face the trade-off between precautionary saving, which is over-investing in risk-free assets, and diversification using risky investments. In addition, since the dynamic model preserves the endogenous uncertainty management mechanism, the diversification benefits are endogenous. Simulation of the model shows that following a policy rate cut, with a strong profitability channel, the bank re-balances the portfolio toward domestic assets. As a result, a prolonged period of low interest rates is accompanied by a persistent increase in home bias, which conforms with what we document in the empirical evidence. To evaluate the macroeconomic consequences of policy rate changes with the presence of global bank lending, we use the complete model with households, production firms, and retail firms, and we introduce nominal rigidity to retail prices. The results show that if banks respond to the decrease in profit by cutting on uncertainty management, the nominal policy rate cut induces a strong portfolio re-balancing effect from the global banks. Since the domestic and foreign economy is symmetric in our model, a decrease in domestic banks' foreign investment is reciprocally reflected as a decrease in capital inflow. This effect sabotages the overall impact of a monetary policy rate cut on output stimulation, as output response following the nominal rate cut decreases by up to 0.5% percent.

Lastly, we examine the empirical evidence on the lending allocation of global banks. The index we use to reflect the allocation pattern is home bias. This index captures the relative preference for domestic assets measured as an under-investment in foreign assets compared to the average level. We collect data on the domestic and cross-border lending of banks from over thirty countries and build country-wise bank home bias since the early 2000s at a quarterly frequency. We find that the overall trend of bank home bias exhibits a V-shaped pattern. Before the crisis, the weighted average bank home bias steadily decreased. The downward trend ceased to continue after the Great Recession, as the home bias level bounced back by over 8% from the historical low and remained high even after the recession ended. The pattern conforms with the recent empirical documentation on the persistent low levels of foreign lending. Moreover, this V-shaped bank home bias is in stark contrast with equity home bias, which has been on a steady decrease during the same period [3].

Literature Our paper relates to the following fields of literature. The first one is international capital flows. Literature has explained how cross-border credit supplies are affected by exchange rates (Cesa-Bianchi et al., 2018; Kekre and Lenel, 2021), liquidity needs (Bruno and Shin, 2015b), regulation (Clayton and Schaab, 2021; Calzolari and Loranth, 2011), and financial crises (Giannetti and Laeven, 2012; Saka, 2017; Albertazzi et al., 2021). Our paper is complementary to the existing literature, as our analysis is not confined to crisis periods and focuses on the general mechanism of monetary policy. The model prediction is also consistent with the recent empirical evidence on the geographical reallocation of bank lending following monetary policy changes (Correa et al., 2018; Granja et al., 2022).

The second strand is monetary policy transmission through financial intermediaries, particularly the bank profitability channel, a novel channel documented in recent empirical evidence (Claessens et al., 2017; Ampudia and Van den Heuvel, 2018; Balloch and Koby, 2019; Eggertsson et al., 2019; Balloch and Koby, 2019; Boungou, 2019; Altavilla et al., 2021). This

[3] For example, McCauley et al. (2021) document that the ratio between outstanding international claims and world GDP decreased from over 60% to approximately 40%. In the European Union, cross-border bank claims have dropped by approximately 25% (Emter et al., 2019).

channel highlights the impact of monetary policy rate adjustments on banks' net interest margin, especially the asymmetric pass-through of the policy rate to deposit and loan rates. While empirical research finds mixed evidence of the impact of this channel on lending, theoretical papers (Wang, 2018; Heider et al., 2019; Ulate, 2021b,a) formalize this channel and highlight that nominal interest rates close to the zero lower bound region suppress bank lending because of low profitability. Our paper incorporates the bank profitability channel by allowing profits to impact banks' risk-taking decisions. To the best of our knowledge, our paper is the first to examine the bank profitability channel in an international environment and to consider the role of second-order moments.

In addition, the feature of endogenous uncertainty in our model can relate to the risk management literature we discussed when introducing the model. In addition, the mechanism can also be understood in two different contexts: monitoring and endogenous information acquisition. For the former, theoretical research like Holmström and Tirole (1993), and Holmstrom and Tirole (1997) develop imperfect information models in which creditors must exert monitoring efforts to observe accurate underlying project returns. Repullo (2004) and Martinez-Miera and Repullo (2020) adapt this setup to banks where investment projects are monitored at a private cost, which is also our crucial assumption. Recent empirical evidence confirms that active bank monitoring can improve the repayment of loans (Branzoli and Fringuellotti, 2020). For the latter, recent research generally assumes that agents can decrease the noise of their investment returns by acquiring additional signals, subject to either pecuniary cost or attention limit (Maćkowiak et al., 2021). This mechanism has been adapted to understand portfolio under-diversification (Van Nieuwerburgh and Veldkamp, 2010; Myatt and Wallace, 2012) and macroeconomic consequences of the uncertainty shock (Fajgelbaum et al., 2017; Straub and Ulbricht, 2015). In particular, De Marco et al. (2022) and Valchev et al. (2017) apply endogenous information to explain international equity portfolio allocation bias. Our paper shares a similar mechanism with these two papers, highlighting the role of information acquisition in determining allocation bias. But in addition to this mechanism, our model also features a bank profitability channel, and this additional channel can help reconcile the difference between equity and bank home bias.

Finally, the predictions of our model add to the recent literature on the consequences of low interest rates. Existing research has established the risk-taking channel of monetary policy, arguing that low rates stimulate the risk-taking behavior of financial intermediaries (Borio and Zhu, 2012; Jiménez et al., 2014; Bruno and Shin, 2015a; Adrian, 2020). However, more recent papers, taking into consideration the impact of low rates on the profitability of banks, find mixed evidence on risk-taking behaviors (Heider et al., 2019; Boungou, 2019). In light of the comprehensive effects of monetary policy, recent theoretical papers characterize multiple channels of policy effect jointly and pin down various forms of interest rate thresholds at which two effects of monetary policy are balanced, i.e., the net interest margin and the asset reevaluation effect (Porcellacchia, 2020), and macroeconomic stability and the financial stability effect (Akinci et al., 2021). Our paper links the profitability effect with risk-taking, demonstrating a novel trade-off between the risk premium effect and the management cost effect.

Layout The rest of the paper proceeds as follows. Section 2.2 provides an analytical model that explains the key mechanisms that determine the global lending preferences of banks, as well as the channels of the impact of monetary policy. In Section 2.3, we adapt the model into a dynamic general equilibrium setup to illustrate the dynamic consequences following a policy rate cut, with the presence of the mechanisms highlighted in Section 2.2. Section 2.4 provides empirical documentation on the home bias in global bank lending. Finally, Section 2.5 concludes.

2.2 Analytical Model

This section outlines our tractable two-country open economy model on global bank lending, taking into consideration the presence of second-order moments and the ability of the bank to manage them.

2.2.1 Setup

Our baseline framework features a bank portfolio model in an open economy with two countries, denoted by (i, j). In each country, the economy consists of three sectors: household, firms and financial intermediaries (banks). For simplicity, we abstract from heterogeneity within sector, so that all sectors are representative. Countries are symmetric and differ only in terms of fundamental parameters. In addition, we assume that there is one common central bank that sets risk-free rates and supply risk-free asset. We abstract away from exchange rates fluctuations in this economy. These assumption can be understood as the characterization of a monetary union, but it can also be seen as a case in which exchange rate fluctuations have been perfectly hedged and there is no risk-free rate arbitrage opportunities. Without loss of generality, we describe the setup from the perspective of country i.

Household There exists a unit measure of identical households. Each household consumes, saves and supplies labor. Households cannot directly invest into assets, they rather save by lending depository funds to financial intermediaries. Workers supply inelastically one unit of labor $l_i^s = 1$ in the local labor market and return their wage earnings to the family. They also choose to hold an amount d_i of local deposits at their bank account at a financial intermediary which is not owned by the family.

Firm The production sector features a representative firm producing a final consumption good with the technology

$$y_i = F(A_i, k_i) = A_i k_i$$

A_i denotes a country specific aggregate technology shock. Moreover, k_i is the aggregate physical capital invested into country $i's$ firms through lending decisions of both countries banks, i.e. $k_i = k_{ii} + k_{ji}$. Aggregate TFP of the two countries (A_i, A_j) follows the structure

$$A_i = z_i \ , \quad \text{and} \quad A_j = z_j \ ,$$

where (z_i, z_j) denote two technology shocks which determine the fundamental component of the respective TFP process. We assume that the random variables (z_i, z_j) are jointly Gaussian distributed with means (μ_{z_i}, μ_{z_j}), variances $(\sigma^2_{z_i}, \sigma^2_{z_j})$, and correlation $\rho \in (-1, 1)$ [4]. As a result, capital returns to production are linear in the fundamental technology component.

In addition to fundamental TFP shock, we assume that there will be a second set of shocks that contribute to the variance of project returns received by the banks, which we refer to as *uncertainty*. Uncertainty shocks, denoted by (ϵ_i, ϵ_j), is Gaussian with zero mean and variance denoted by $(0, \sigma^2_\epsilon)$. Moreover, we impose that (ϵ_i, ϵ_j) is independent from (z_i, z_j). The economic intuition of this component is that it captures the non-fundamental risky components of project returns, such as information friction, regulatory frictions or policy uncertainty. Since it is not fundamental, we assume that it can be reduced by the bank through *management* activ-

[4] This assumption tells us that return on projects can potentially be negative. This is to make analytical solution tractable. In the numerical exercise, we will choose parameters such that negative returns are of very little possibility.

ity, but with a cost. This can be understood as banks hiring more project managers to oversee their loans in order to reduce the possibility of default. The details of this specification will be introduced in Bank and Interest Rates Determination section.

Bank Bank is the only financial intermediation of our economy. We assume that there is one representative banking sector in each country, who performs both domestic and foreign lending. The asset side of the banks' balance sheet thus includes loans to domestic firm project, loans to foreign project, and one risk-free asset. We assume that the risk-free asset is the same for both countries with gross return R^f. The liability side is assumed to include only equity and deposit. The bank is endowed with initial equity e_i, and deposit d_i is supplied uniquely by domestic households. The size of the balance sheet, or the bank's total loanable wealth, is thus given by $w_i = e_i + d_i$. Denote $\delta = \frac{d_i}{w_i}$ as the deposit-to-asset ratio.

We adopt the portfolio approach of banking and assume that the banks have CARA preferences of the standard form

$$u(e_i) = -\frac{1}{\alpha} e^{-\alpha e_i} \ ,$$

where $\alpha > 0$ denotes the absolute risk aversion parameter. The reason why we choose this specification of bank utility is two-fold. First of all, since we seek to capture the risk-taking channel of monetary policy in our model, the CARA-normal framework is a convenient form since it allows us to develop tractable portfolio solutions conditioning on both first and second-order moment of the investment projects. Second of all, although many banking literature assume risk neutrality of banks, risk also plays an important role in these model, through the risk-weighted capital requirement constraint. Therefore, the risk-aversion of banks in our framework can also arise from similar motives to control for riskiness.

Central Bank We assume that there exists one central bank, whose role is to determine risk-free return R^f, which is the same across both countries, and set regulatory policies. The risk-free asset can thus be understood as reserves directly provided by the central bank, or other form of safe asset whose return is under the influence of central bank operations.

Interest Rates Determination Beside the risk-free interest rate chosen by the central bank, there are two additional interest rates in our economy, the deposit rate and the loan rates. We assume that both rates depends on the risk-free rate, and we specify the degree of pass-through. The deposit rate offered by the bank is R^d. For simplicity, we assume that the deposit rate is a functional of the gross monetary policy rate R^f. Specifically, we impose $R^d = \left(R^f\right)^{\omega}$, where $\omega \in \left[0, \delta^{-1}\right]$ denotes the pass-through elasticity from the risk-free monetary policy rate to the deposit rate. The previous parametric specification serves as short-cut to model deposit competition in a low interest rate environment. Consistent with empirical evidence, ω takes a value close to zero at the ZLB. Away from the ZLB, ω is close to its upper bound of unity.

The loans rates charged by the banks are determined in two steps. Given the gross return (R^i, R^j) of the risky projects and the risk-free rate R^f, banks bargain with entrepreneurs over the division. Specifically, we assume that banks have bargaining power $\theta \in (0, 1]$, and entrepreneurs have respectively bargaining power $1 - \theta$. The standard Nash bargaining outcome predicts that equilibrium loan rates are given by

$$\bar{R}^l_{ii} = \theta \left(R_i - R^f\right) + R^f \ , \quad \text{and} \quad \bar{R}^l_{ij} = \theta \left(R_j - R^f\right) + R^f \ ,$$

If $\theta = 0$, there is complete pass-through of policy rate to loan rates. On the contrary, if $\theta = 1$, there is no pass-through and banks completely extract matching returns. Moreover, as stated in previous section, there are non-fundamental uncertainty shocks (ϵ_i, ϵ_j) that affect project returns received by the bank. To be more specific, we assume that the bargained outcome $(\bar{R}^l_{ii}, \bar{R}^l_{ij})$ is subject to the perturbation of uncertainty shocks, i.e.

$$R^l_{ii} = \bar{R}^l_{ii} + \epsilon_i \ , \qquad R^l_{ij} = \bar{R}^l_{ij} + \epsilon_j \ ,$$

where ϵ_i, ϵ_j are uncertainty of the respective country.

In addition, we assume that the uncertainty can be reduced through costly management [5]. By choosing effort levels (m_{ii}, m_{ij}), the bank can decrease the size of the uncertainty shock

$$R^l_{ii} = \bar{R}^l_{ii} + \mathcal{P}(m_{ij}, k_{ii})\epsilon_i \ , \qquad R^l_{ij} = \bar{R}^l_{ij} + \mathcal{P}(m_{ij}, k_{ii})\epsilon_j \ ,$$

with $\mathcal{P} \in (0, 1)$ is the uncertainty reduction technology, or *management*, of the banks, and

[5] The assumption of costly uncertainty management stems from multiple strands of literature, in particular risk management and monitoring, and endogenous information acquisition. The difference from the monitoring literature (Holmstrom and Tirole, 1997; Repullo, 2004) is that these models often assume monitor shifts the probability distribution of project realization, changing the mean and the variance at the same time. In our setup, management only affects variance directly. Endogenous information acquisition literature (Van Nieuwerburgh and Veldkamp, 2010) points out costly information acquisition as one reason for portfolio under-diversification. Essentially, investors would like to learn more about the assets which they hold the most, and the act of learning in turn may strengthens the investors' incentives to increase the holdings. Our assumption of comparative advantage in monitoring also features this effect

it depends on m_j, the effort level of managing, and the loan size. The costs associated with management activities for domestic and foreign loans are given by $\mathcal{C}_i(m_{ii}, k_{ii}, \Delta\tilde{e}_i{}')$ and $\mathcal{C}_j(m_{iij}, k_{ij}, \Delta\tilde{e}_i{}')$ respectively. The cost functions are assumed to be different for the domestic and foreign assets to reflect the comparative advantage of bank's in managing their domestic lending. Equivalently speaking, foreign lending always poses greater difficulty in managing, i.e. $\mathcal{C}_{i,m}(m, k, \Delta\tilde{e}_i{}') \leq \mathcal{C}_{j,m}(m, k, \Delta\tilde{e}_i{}')$ for all levels of $(m, k, \Delta\tilde{e}_i{}')$ [6]. To simplify the analysis, we assume that domestic uncertainty cost is always zero. That is, $\mathcal{C}_i(m, k, \Delta\tilde{e}_i{}') = 0$ for all levels of m. As a result, domestic uncertainty can be perfectly eliminated, as $\mathcal{P}(m_i, k_{ii}) = 0$. This is equivalent to saying that we focus not on the absolute level of uncertainty, but the relative level of uncertainty difference in domestic and foreign investments.

The crucial assumption here is the fact that the management cost is dependent on the bank's profit, measured by the expected equity gains $\Delta\tilde{e}_i{}')$[7]. This is an ad hoc way to capture the fact that costly uncertainty management is not exogenous to banks' investment decisions, consistent with the common assumption in bank risk management literature. For example, (Froot and Stein, 1998) provides a joint framework analyzing the portfolio allocation and risk management with the presence of illiquid risk, in which capitals are used as a device to absorb illiquid risks. As a result, optimal portfolio allocation must be determined jointly across assets instead of individually. Rampini and Viswanathan (2013), studying firms' risk management, shows that firms with low cash flows make cutbacks in risk management. Our assumption here seeks to characterize an effect in a similar spirit, and this ad hoc form of assumption can be micro-founded if we also incorporate a convex cost in raising external capital for further investment. In addition, the assumption is also consistent with empirical evidence. Ellul and Yerramilli (2013) construct risk management index (RMI) on the level of bank holding companies and find that more profitable banks have a higher degree of risk management.

Timing of Events Timing of events is summarized in Figure 2.1.

0. *Depositing collection.* Households deposit their money into respective domestic bank, given the *gross* deposit rate R^d.

1. *Portfolio investment.* Bank chooses the portfolio allocation $\{k_{ii}.k_{ij}, b_i\}$, given the available

[6] Apart from comparative advantage, moral hazard issues, as pointed out by Farhi and Tirole (2012), also explain why banks face uncertainty in foreign investments but not their domestic counterpart. Banks might count on explicit bail-out by the government on the domestic borrowers defaulting on the loans but not the foreign borrowers.

[7] Here the equity gain is *before* uncertainty management costs. The cost is wasted in the sense that it is not redistributed back to households.

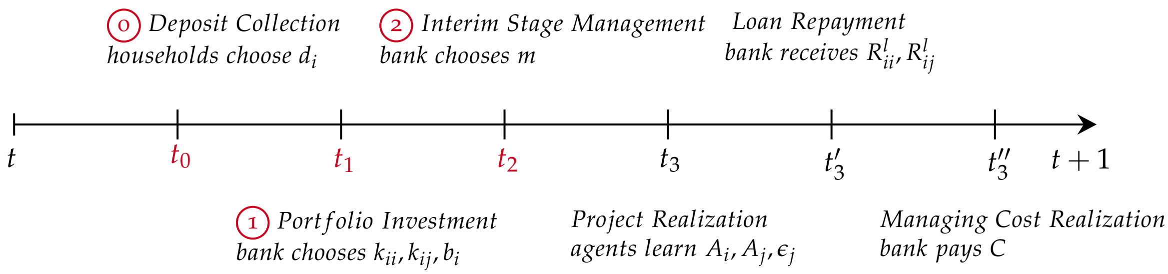

Figure 2.1: Timing of events.

funds w_i, which is the sum of the initial equity e_i and deposit received d_i.

2. *Interim stage management.* Given the portfolio $\{k_{ii}.k_{ij}, b_i\}$, bank choose the optimal level of management m to exert to reduce uncertainty in foreign investment.

2.2.2 Bank's Problem

Under this setup, we can define the end-of-period equity before the management cost realization, denote as $e_i{}'$:

$$\tilde{e}_i{}' = \underbrace{R^f b_i}_{\text{risk-free repayment}} + \underbrace{R^l_{ii} k_{ii}}_{\text{domestic loan repayment}} + \underbrace{R^l_{ij} k_{ij}}_{\text{foreign loan repayment}} - \underbrace{R^d d_i}_{\text{deposit payment}} .$$

Based on $\tilde{e}_i{}'$, we define *Bank profitability* as increment of equity before managing cost

$$\Delta \tilde{e}_i{}' = \tilde{e}_i{}' - e_i.$$

And after the management cost has realized, we have the final end of period equity:

$$e'_i = R^l_{ii} k_{ii} + \Big(\bar{R}^l_{ij} + \epsilon_j \big(1 - \mathcal{P}(m^*, k_{ij})\big) \Big) k_{ij} + r^f b_i - R^d d_i - \mathcal{C}(m^*, k_{ij}, \Delta \tilde{e}_i{}') .$$

Note that under this setup, we can redefine the expected profitability as follows

$$\mathbb{E}\left[\Delta \tilde{e}'_i | \mathcal{I}\right] = \underbrace{(1 - \omega\delta) w_i r^f}_{\text{risk-free profit}} + \underbrace{\theta(\mu_i - r^f) k_{ii}}_{\text{risky domestic profit}} + \underbrace{\theta(\mu_j - r^f) k_{ij}}_{\text{risky foreign profit}} . \tag{2.2.1}$$

where (μ_i, μ_j) are the net return from the project, r_f is the net risk-free rate, and $\mathcal{I}$ contains all the information regarding portfolio allocation. This expression shows that the expected profitability essentially, contains two component. The first component, risk-free increment, denote the profit coming from the interest rate margin. As the bank pays the depositors at a lower rate than risk-free rate, and the deposit-to-asset ratio δ is always less than 1, this part is what banks can *arbitrage* between depositors and risk-free asset issuer, i.e. the central bank. The second component, which we refer to as risky increment, comes from the risk premium of domestic and foreign investment. θ is the Nash bargaining parameter that determines to what extent this part can be extracted by the bank. We can see that the risk-free interest rate has positive effect on the first component and negative impact on the second. The following lemma characterizes the overall impact of monetary policy.

Lemma 1 (Expected Bank Profit and Monetary Policy). *Assume that the two countries' TFP shocks have the same mean, i.e. $\mu_i = \mu_j = \mu$. Denote the domestic risky asset share by κ_{ii}, respectively the cross border risky asset share by κ_{ij}. A monetary policy tightening increases expected bank profitability $\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]$ if the following condition holds*

$$\frac{b_i}{w_i} \geq \frac{\theta + \omega\delta - 1}{\theta} - \frac{\mu - r^f}{r^f}\left(\varepsilon_{k_{ii},r^f}\kappa_{ii} + \varepsilon_{k_{ij},r^f}\kappa_{ij}\right) \ , \tag{2.2.2}$$

where ε_{k_{ii},r^f} and ε_{k_{ij},r^f} denote elasticities of risky asset investments with respect to the net monetary policy rate.

To understand the result of Lemma 1, notice that the left hand side of equation (2.2.2) denotes the share of risk-free central bank reserve hold by banks of country i. The right hand side is composed of two terms. The first term denotes the *mechanical effect* of a monetary policy tightening. It reflects the change in expected bank profitability holding the current portfolio unchanged. Contrary, the second term documents the *behavioral effect* of a monetary policy tightening. It reflects the change in expected profitability induced by a change in the portfolio composition in response to the policy change.

The mechanical effect trades off two channels: First, a standard bank lending channel according to which a monetary policy tightening reduces the excess return on risk asset investments. The strength of this channel is captured by banks' bargaining power θ. Second, a net risk-free return exposure channel according to which a monetary policy tightening increases the return margin between central bank reserve holdings and deposit rates, which is captured by the leverage ratio δ and the deposit elasticity ω. For larger values of δ, θ and ω, a larger risk-free asset share is required for expected bank profitability to increase. The intuitions are as follows: an increase in the leverage ratio δ exposes banks to larger amounts of deposit return payments and hence decreases profits. For expected profitability to increase by compensating for the bank lending channel, a larger central bank reserve share is necessary. Moreover, an increase in pass through of monetary policy to deposit rates ω increases the deposit rate and reduces profitability. As a result, a larger central bank reserve share is required to compensate for the negative margin arising from the standard bank lending channel. If the economy is close to the ZLB, i.e. ω is close to zero, the mechanical effect will always induce an increase in expected bank profitability as $\omega < \delta^{-1}(1-\theta)$ in this case. Finally, an increase in the bargaining weight θ for loan rates strengthens the mechanical effect arising from the standard bank lending channel by reducing the expected bank profitability.

The behavioral effect implies that a monetary policy tightening decreases excess returns of loans and hence reduces risky asset holdings. This goes along with a reduction is expected profitability which requires in turn a higher central bank reserve share to compensate for the downward pressure arising from the bank lending channel. The elasticities $(\varepsilon_{k_{ii},r^f}, \varepsilon_{k_{ij},r^f})$ also encompass endogenously substitution effects among risk asset holdings in response to changes in the monetary policy environment and hence reflect the change of the home bias of banks. The former channel is relevant for expected bank profitability in case of loan rate heterogeneity across countries, i.e. if $\mu_i \neq \mu_j$ applies.

We are now ready to define the bank's problem under this setup. The objective of the multistage problem can be written as

$$\max_{\{k_{ii},k_{ij},b_i,m\}} \mathbb{E}\left[u(e_i')|\mathcal{I}\right] \qquad s.t. \tag{P1}$$

$$e_i' = R_{ii}^l k_{ii} + \left(R_{ij}^l + \epsilon_j\big(1-\mathcal{P}(m,k_{ij})\big)\right)k_{ij} + r^f b_i - R^d d_i - \mathcal{C}(m,k_{ij},\Delta\tilde{e}_i{}') \; ,$$

$$w_i = k_{ii} + k_{ij} + b_i$$

where $(R_{ii}^l, R_{ij}^l, r^f)$ denote the gross returns of investment opportunities. The maximization problem of banks is solved by backward induction. Given $\mathcal{I}$, they maximize expected utility, which depends on terminal equity e_i'.

2.2.3 Interim Stage Management

Given the timeline of events, we solve the banks' optimization problem (P1) by backward induction. At second stage, bank has chosen the portfolio $\{k_{ii}.k_{ij}, b_i\}$ and need to exert an effort to control for the detrimental effect of uncertainty. Banks can reduce the uncertainty σ_ϵ^2 by choosing, for a given cross-border investment level k_{ij}, an effort level m^* to maximize expected utility gains

$$m^* = \arg\max \mathbb{E}\left[u\left(\epsilon_j \mathcal{P}(m, k_{ij})k_{ij} - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}')\right)|\mathcal{I}\right] \;, \tag{2.2.3}$$

where $\mathcal{P}(m, k_{ij})$ is the uncertainty reduction function and $\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}')$ is the uncertainty management cost function defined in previous section. We parameterize the uncertainty reduction function and management cost function $\mathcal{P}(m, k_{ij})$ in an elasticity form

$$\mathcal{P}(m, k_{ij}) = m^{-\varphi} k_{ij}^{\eta} \;, \qquad \text{with} \quad \varphi > 0,\ \eta > 0 \tag{2.2.4}$$

$$\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}') = \left(1 - \psi \mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda} m^{\chi} k_{ij}^{\nu} \;, \quad \text{with} \quad \psi \in \Psi,\ \lambda \geq 0,\ \chi > 1,\ \nu > 0 \;, \tag{2.2.5}$$

where Ψ is the feasible set for the sensitivity parameter ψ, formalized in the appendix. Under this formulation, the parameters $(\varphi, \eta, \lambda, \chi, \nu)$ all have direct interpretations, as they denote the elasticities of the *effective* uncertainty reduction and management cost with respect to the respective inputs. Assumption 1 characterizes the key property we assume of the management cost function.

Assumption 1 (Uncertainty Management Costs)**.** *We assume that uncertainty management costs $\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}')$ decrease in expected bank profitability, i.e. $\psi \in \Psi \subset \mathbb{R}_+$.*

Assumption 1 limits the support of ψ, which denotes the sensitivity of the uncertainty management cost with respect to expected bank profitability. This implies that the cost of uncertainty management is endogenously affected by banks' investment decisions. The assumption is in a similar spirit to the corporate finance models that feature a interim stage liquidity shocks. In this type of models, after investing money in the first period and before the project return realizes, banks or investors need to secure new funds for interim stage liquidity needs. The amount of new funds that can be raised depends either on some collateral or on the pledgeable part of future project return realization, and the latter is just what we assume. At the uncertainty management stage, banks have already invested their total available funds w_i. Hence, to conduct uncertainty management activities they need to borrow additional funds, which they repay at the end of the period. We assume that the counterparty lender is risk neutral, makes zero profits and offers a contract in which the interest rate depends on the expected profitability of bank activities. For simplicity, we abstract from modeling a full-blown inter-bank market equilibrium. Instead, we simply assume that the interest rate charged for borrowing at interim stage decreases in the expected profitability of banking activities, as higher expected profitability implies higher pledgeable return. From a modelling perspective, this specification also introduces a wealth-dependent component into the portfolio choice problem of banks.

The result of the second-stage uncertainty management problem is summarized in the following Lemma 2.

Lemma 2 (Optimal uncertainty management). *Given the first stage investment $\{k_{ii}, k_{ij}, b_i\}$, the variance of foreign loans under optimal effort level m^* is given by*

$$\underbrace{\sigma_j^2}_{\text{① TFP Shock Variance}} + \underbrace{\zeta_i \big(1 - \psi \mathbb{E}\left[\Delta \tilde{e}_i{}' | \mathcal{I}\right]\big) \times \frac{1}{k_{ij}}}_{\text{Management reduction}} \times \underbrace{\sigma_\epsilon^2}_{\text{② Uncertainty Shock Variance}},$$

where (ζ_i, ψ) are the coefficients determined by the parametrization of the uncertainty reduction function $\mathcal{P}(m, k_{ij})$ and the cost function $\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}')$.

Lemma 2 shows that the size of the *ex post uncertainty*, i.e. the uncertainty regarding cross-border investment returns after banks have exerted effort to reduce its size, depends on *ex ante uncertainty* σ_ϵ^2. In addition, it also depends one three key components. First, it depends on the parameter ζ_i, which we refer to as inverse uncertainty management ability. It is a scaled version of the managing cost shifter c_i. The scaling term in turn hinges on the management costs and uncertainty reduction elasticities as well as the banks inherent risk aversion. The lower the value of ζ_i, the lower is the ex post uncertainty. Second, ex post uncertainty depends negatively on the expected profitability before uncertainty management costs. The degree of this reduction in turn increases in the sensitivity parameter ψ, as imposed in 1. Third, ex post uncertainty depends negatively on the total size of cross border investment k_{ij}, in the sense that there is return to scale effect in uncertainty management. Several theories in the literature can explain this return to scale effect, i.e. a negative correlation between asset size and asset risk. For example, it might arise from a moral hazard problem between banks and regulators, i.e. due to too big to fail incentives. Farhi and Tirole (2012) point out strategic complementarities in balance-sheet risk choices due to ex post bailouts. In our model, an increase in cross border asset holdings increases overall risky asset holdings of the banking sector. In the light of the *too big to fail* argument, this raises the likelihood to receive governmental bailouts in case of failure, which is in turn equivalent to a decrease in risks.

Before we move on to the first stage portfolio allocation problem, we state two corollaries of comparative statics of the optimal management effort m^* and reduced form management efficiency paratmer ζ_i with respect to the elasticity parameters.

Corollary 1 (Comparative Statistics of Optimal Management Effort)**.** *The key comparative statics of optimal managing effort m^* satisfy*

$$\frac{dm^*}{d\alpha} > 0\,, \quad \frac{dm^*}{d\sigma_\epsilon^2} > 0\,, \quad \frac{dm^*}{dk_{ij}} \gtrless 0\,,$$

Under the functional forms specified in Lemma Uncertainty and Assumption Elasticity, optimal risk management effort m^* are characterized by the following properties:

(a) If $\psi = 0$, i.e. risk management costs are insensitive to expected bank profitability, m^* is strictly increasing and concave in cross border investment k_{ij}.

(b) If $\psi > 0$, i.e. risk management costs are sensitive to expected bank profitability, m^* is strictly increasing and admits an inverse S-shape in cross border investment k_{ij}.

The sign of the comparative statics with respect to the first stage investment k_{ij} is arbitrary. This is due to the assumption that managing costs may be increasing in initial investments.

We graphically illustrate Corollary 1 in Figure 2.4. It can be seen that optimal uncertainty management effort under $\psi > 0$ constitutes an upper envelop of optimal uncertainty management effort under $\psi > 0$. Consequently, the case of $\psi > 0$ limits the uncertainty friction faced by banks, and thus strengthens portfolio diversification incentives.

The intuition for the first part of Corollary 1 is straightforward. If uncertainty management costs are independent of expected bank profitability. This ensures that optimal uncertainty management effort m^* is concave in cross border investment k_{ij}. However, in the presence of decreasing uncertainty management costs with respect to expected bank profitability, a countervailing increasing returns to scale channel is at work. A larger cross border investment position increases expected bank profitability, which translates into a larger reduction on uncertainty management costs due to $\lambda > 1$. This channel induces a more than proportional increase of optimal uncertainty management effort. As the DRS channel is strong for small cross border positions, whereas the IRS channel is especially pronounced for larger cross border positions, the shape of optimal uncertainty management effort m^* follows a combination of both channels. It is thus concave for small cross border positions and convex for large cross border positions.

Corollary 2 (Comparative Statistics of Managing Ability). *Under the functional forms specified in Lemma Uncertainty and Assumption Elasticity, the key comparative statics of the inverse risk management ability ζ_i are given by*

$$\frac{\partial \zeta_i}{\partial \alpha} < 0 \, , \quad \frac{\partial \zeta_i}{\partial \varphi} < 0 \, , \quad \textit{and} \quad \frac{\partial \zeta_i}{\partial c_i} > 0 \, .$$

Additionally, the comparative statics with respect to the risk reduction elasticity η and the management cost elasticity ν are hump-shaped such that

(a) $\frac{\partial \zeta_i}{\partial \eta} \geq 0$ *if* $\eta \geq \underline{\eta}$, *respectively* $\frac{\partial \zeta_i}{\partial \eta} < 0$ *if* $\eta < \underline{\eta}$,

(b) $\frac{\partial \zeta_i}{\partial \nu} \geq 0$ *if* $\ln(\alpha\varphi) \geq -2(1+\eta)$. *Moreover, if* $\ln(\alpha\varphi) < -2(1+\eta)$ *holds, we have* $\frac{\partial \zeta_i}{\partial \nu} \geq 0$ *if* $\nu \geq \underline{\nu}$, *respectively* $\frac{\partial \zeta_i}{\partial \nu} < 0$ *if* $\nu < \underline{\nu}$.

Comparative statics for the parameters (α, φ, c_i) follow intuitively. An increase in banks' risk aversion induces higher uncertainty management effort and thus improves their managing ability. A rise in the uncertainty reduction elasticity with respect to uncertainty management φ improves the efficacy of uncertainty management and hence lowers ζ_i, whereas an increase in the marginal cost shifter c_i weakens the managing ability. However, comparative statics with respect to (η, ν) are non monotonous due to the presence of two countervailing effects: an increase in η, which captures the complementarity strength between first stage cross border investment and managing effort, lowers the uncertainty reduction ability through $\mathcal{P}(m, k_{ij})$. A rise in η however also lowers the degree of convexity of the uncertainty management cost function $\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}')$. For large values of η the latter effect dominates and the result follows. A similar reasoning applies to the comparative static with respect to ν. At impact an increase in ν raises uncertainty management costs, but also reduces the degree of convexity.

2.2.4 Portfolio Solution

Given the derivation of optimal uncertainty management effort, we restate the maximization problem of banks (P1) in an equivalent form, (P1′). We prove in the appendix that the solution to the banks' maximization problem (P1) is equivalent to the solution to

$$\max_{\{k_{ii},k_{ij},b_i\}} \mathbb{E}\left[u(e_i')|\mathcal{I}\right] \qquad s.t. \tag{P1'}$$

$$e_i' = R_{ii}^l k_{ii} + R_{ij}^l k_{ij} + r^f b_i - R^d d_i \ ,$$

$$w_i = k_{ii} + k_{ij} + b_i \ ,$$

where the variance of a per unit cross-border investment is given in Lemma 2. In Proposition 1 we characterize the optimal portfolio allocation of banks.

Proposition 1 (Optimal Portfolio Allocation). *Given the optimal management of uncertainty in the second stage, the optimal portfolio allocation chosen by the bank satisfies*

$$k_{ii} = \left(1-\tilde{\rho}^2\right)^{-1}\left(\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{\tilde{\rho}\tilde{\sigma}_j}{\sigma_i}\frac{\theta(\mu_j - r^f)}{\alpha\tilde{\sigma}_j^2} + \frac{\tilde{\rho}\tilde{\sigma}_j}{\sigma_i}\frac{\frac{1}{2}\zeta_i\tilde{\sigma}_\epsilon^2}{\tilde{\sigma}_j^2}\right),$$

$$k_{ij} = \left(1-\tilde{\rho}^2\right)^{-1}\left(\frac{\theta(\mu_j - r^f)}{\alpha\tilde{\sigma}_j^2} - \frac{\tilde{\rho}\sigma_i}{\tilde{\sigma}_j}\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{\frac{1}{2}\zeta_i\tilde{\sigma}_\epsilon^2}{\tilde{\sigma}_j^2}\right).$$

where

$$\tilde{\sigma}_\epsilon^2 = \sigma_\epsilon^2\left[1-\psi(1-\omega\delta)w_i r^f\right] \ ,$$

$$\tilde{\sigma}_j^2 = \sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 \ ,$$

$$\tilde{\rho} = \frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)}{\sigma_i\tilde{\sigma}_j} \ .$$

To better understand the intuition of Proposition 1, notice first that if $\sigma_\epsilon^2 = 0$, i.e. the uncertainty in foreign investment can be perfectly eliminated, the third terms inside the second bracket of k_{ii} and k_{ij} disappear. Furthermore, the expression of $(\tilde{\sigma}_j^2, \tilde{\rho})$ will collapse to the original (σ_j^2, ρ). In this case, the solution becomes that of a standard CARA-Normal problem, with the first component denoting the baseline CARA portfolio choice characterized by the Sharpe ratio, and the second component denoting a diversification channel governed by the correlation ρ between two countries fundamentals. In this case, monetary policy affects bank's investment decision only through risk-premium, and the risk-taking channel of monetary policy is at work.

If $\sigma_\epsilon^2 \neq 0$, but $\psi = 0$, we have the case in which there is foreign investment uncertainty, but the cost of managing is exogenous. This is due to the fact that when $\psi = 0$, the cost of management does not depend on expected future profit, as can be seen from Lemma 2. In this case, the third terms appear in the expression, but the expression of $(\tilde{\sigma}_\epsilon^2, \tilde{\sigma}_j^2, \tilde{\rho})$ will collapse to the original $(\sigma_\epsilon^2, \sigma_j^2, \rho)$. We see that with the presence of uncertainty, foreign investment k_{ij} is biased downwards as the third term is always negative. Whereas the impact of domestic investment is ambiguous, as it depends on the correlation ρ. This result is intuitive, as the presence of uncertainty would always make foreign investment less attractive, therefore bank would reduce foreign lending. Whether domestic lending would be reduced depends on the diversification merit, which in turn depends on the fundamental correlation ρ. If the two countries' fundamental is positively correlated, domestic and foreign investments are substitute, thus domestic lending would increases with the presence of foreign uncertainty. If $\rho < 0$, there is complementarity between two assets as there is the merit of diversification. Therefore, domestic lending will also goes down, although to a less extent than foreign lending. In this case, monetary policy still work through risk-taking channel but does not interact with the uncertainty management.

When $\psi \neq 0$, the interaction between monetary policy and uncertainty begins to kick in, as three new channels of monetary policy is introduced. The first channel, which works through $\tilde{\sigma}_\epsilon^2$, is the *attenuation of uncertainty friction* channel. As can be seen from the expression of $\tilde{\sigma}_\epsilon^2$, the presence of the cost reduction mechanism, i.e. $\psi \neq 0$, makes the uncertainty friction less relevant. The derivative of this channel of effect with respect to interest rate is always negative, meaning that the higher the interest rate, the lower the effective uncertainty variance. This is consistent with the intuition, as higher interest rate implies higher rate-free rate and deposit rate margin, which in turn implies higher profitability from the risk-free rate component, as shown in Equation 2.2.1, and thus lowers the cost of management.

The second channel, which works through $\tilde{\sigma}_j^2$, is the *variance reduction* channel for foreign investment. This comes from the fact that uncertainty management has economy of scale, because the risk premium of the return adds to the expected profitability. This leads to less cost for uncertainty management and lower ex post variance after management, which further increases the investment for foreign investment. The derivative of this channel of effect with respect to interest rate is always positive, meaning that the higher the interest rate, the higher the effective fundamental variances. This is consistent with the intuition, as higher interest rate implies lower risk premium for the foreign asset. This leads to less expected profits from the risky increment component, as shown in Equation 2.2.1, and therefore less variance reduction effect for foreign investment.

The third channel, which works though $\tilde{\rho}$, is what we refer to as *generalized correlation structure* channel. This term reflects the de facto correlation between domestic foreign asset, which is different from the fundamental correlation ρ. The reason is that since risky returns from domestic projects can be used to lower the cost of uncertainty management of foreign investment, this creates an additional layer of correlation similar to the idea of cross-subsidization. This can be linked to the effect of interdependent investment decisions highlighted in Froot and Stein (1998). The interdependence comes from the endogeneity of the risk-aversion in Froot and Stein (1998), and in our case, it comes from the endogenous uncertainty management cost. However, the underlying mechanism is very similar, that is, price of non-tradeable risks is essentially endogenous.

Whether $\tilde{\rho}$ increases or decreases in the risk-free rate is not straightforward to see, as both the numerator and the denominator contains r^f. However, note that the numerator is decreasing in r^f, which means that the de facto covariance of the two assets is always decreasing in risk-free rate, and the correlation will be jointly pinned down by this new covariaince and new variance $\tilde{\sigma}_j^2$. The reason why de facto covariance is decreasing in risk-free rate is because the new layer of correlation depends on the risky return of the domestic investment captured by its risk premium. Thus the higher the risk-free rate, the weaker this new channel of covariance.

The relationship between the new transmission channels of monetary policy and the pledgeablity future profits can be seen from the following corollary.

Corollary 3 (Asset Pledgeablity)**.** *Suppose that different components of expected bank profitability have different degree of pledgeablity, differentiated by κ_d and κ_f:*

$$\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right] = \underbrace{(1-\omega\delta)w_i r^f}_{\text{risk-free profit}} + \underbrace{\kappa_d\theta(\mu_i - r^f)k_{ii}}_{\text{risky domestic profit}} + \underbrace{\kappa_f\theta(\mu_j - r^f)k_{ij}}_{\text{risky foreign profit}} .$$

where $\kappa_d \in [0,1]$ and $\kappa_f \in [0,1]$ denotes the difference in pledgeablity of risky domestic and foreign returns comparing to risk-free returns. Then for the portfolio solution, we have the following definition of the parameters:

$$\begin{aligned}
\tilde{\sigma}_\epsilon^2 &= \sigma_\epsilon^2\left[1-\psi(1-\omega\delta)w_i r^f\right] , \\
\tilde{\sigma}_j^2 &= \sigma_j^2 - \kappa_f\zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 , \\
\tilde{\rho} &= \frac{\left(\rho\sigma_i\sigma_j - \frac{\kappa_d}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)}{\sigma_i\tilde{\sigma}_j} .
\end{aligned}$$

Finally, before we proceed to examine the implication of monetary policy on bank home bias, we state the condition to ensure the existence of a global maximum for the policy functions derived in Proposition 1. we characterize in Lemma 3 the feasible parameter space Ψ^{GM} of banks' uncertainty management cost reduction sensitivity parameter ψ. The upper bound on the managing costs sensitivity parameter is also illustrated in Figure 2.15.

Lemma 3. *$\Phi(\psi)$ is discontinuous at the point*

$$\psi^{dc} = \frac{\sigma_j^2}{\zeta_i \theta (\mu_j - r^m) \sigma_m^2} .$$

(a) If $2\rho \frac{\mu_j - r^m}{\sigma_j} = \frac{\mu_i - r^m}{\sigma_i}$, $\Phi(\psi)$ is an affine function in ψ in $\mathbb{R}_+$ if $2\frac{\sigma_i}{\sigma_j} \geq \frac{\mu_i - r^m}{\mu_j - r^m}$.

(b) If $2\rho \frac{\mu_j - r^m}{\sigma_j} \neq \frac{\mu_i - r^m}{\sigma_i}$, $\Phi(\psi)$ has a positive and a negative root, between which the function is positive. Thus, there exists an upper bound $\overline{\psi}^{GM}$ on ψ, such that Φ is strictly positive in the set $\Psi^{GM} \equiv \left[0, \overline{\psi}^{GM}\right)$. The upper bound is given by

$$\overline{\psi}^{GM} = \Gamma\left(\left[\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)\right] + \left(\left[\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)\right]^2 + (\mu_i - r^m)^2(1-\rho^2)\sigma_j^2 \right)^{\frac{1}{2}} \right),$$

with $\Gamma \equiv \frac{2\sigma_i}{\zeta_i \theta \sigma_m^2 (\mu_i - r^m)^2}$. $\overline{\psi}^{GM} < \psi^{dc}$

The first statement in Lemma 3 provides a condition under which the auxiliary function Φ is affine in ψ and strictly positive. Consequently, the sensitivity of the cost function with respect to expected bank profitability is unrestricted in this case. The second statement of Lemma 3 considers the case in which Φ is nonlinear in ψ. In this case, the solution describes a global maximum if $\psi < \overline{\psi}^{GM}$. The necessity of the upper bound is required to prevent banks from exploiting uncertainty management activities and taking advantage of the cross-border information friction. From Corollary 1 we know that uncertainty management activities follow an inverse *S*-shape in cross-border investment. banks thus find it optimal to choose an allocation on the increasing returns to scale part if the sensitivity of the cost reduction with respect to expected profitability is large. In the light of the previous argument, the derived upper bound $\overline{\psi}^{GM}$ hence precisely limits banks uncertainty management incentives.

2.2.5 Monetary Policy Transmission

Based on the optimal bank portfolio characterization from Proposition 1, we now define the theoretical counterpart to our empirical bank home bias measure. To do so, we fist impose two assumptions, which simplify the analysis of home bias fluctuations without changing the model propagation itself fundamentally.

Assumption 2 (Safe Asset Provision). *Safe assets are provided by country i, i.e. risk-free asset holdings are domestic from the perspective of country i, not from the perspective of country j.*

Under Assumption 2, the theoretical counterpart to the empirical home bias measure for country i is given by

$$\mathcal{HB}_i = 1 - \frac{1 + \frac{w_j}{w_i}}{1 + \frac{k_{jj}}{k_{ij}}} . \tag{2.2.6}$$

It can be seen from the previous equation (2.2.6) that our home bias measure essentially boils down to relating two ratios: it strictly decreases in the ratio of initial bank wealth $\frac{w_j}{w_i}$, and strictly increases in the ratio of investments into the counterparty country j, i.e. $\frac{k_{jj}}{k_{ij}}$. As the safe asset is domestic from the perspective of country i, the home bias measure is independent from risk-free asset holdings. Therefore, the measure only reflects preferences over *productive assets* and is not affected by the demand for safe assets.[8] In Appendix 2.7.1, we derive theoretical bank home bias measures when relaxing Assumption 2 and numerically show how the subsequent results depend on the applied home bias measure. Before stating the first main result on how monetary policy shapes bank home bias, we constrain in Assumption 3 the fundamental model parameters across countries.

Assumption 3 (Symmetry between Countries). *The fundamental model parameters of both countries are equal, i.e. $\mu \equiv \mu_i = \mu_j$, $\sigma \equiv \sigma_i = \sigma_j$, $\zeta \equiv \zeta_i = \zeta_j$ and $w \equiv w_i = w_j$ holds.*

Assumption 3 eliminates the role of cross country heterogeneity for the determination of home bias. It thus allows to isolate the effects being of interest, namely the interaction of cross-border information frictions and monetary policy. Assumptions 2 and 3 are necessary to analytically characterize bank home bias fluctuations in our model environment.

Apart from these two assumptions, we have the following lemma to ensure that the model prediction is consistent with general stylized facts regarding cross-border lending.

[8] The incentives of investors to hold safe assets when the economic uncertainty is high have been addressed by the flight to safety (FTS) literature. Caballero and Farhi (2018) discuss the consequences of safe asset shortage and the role of public debt. Brunnermeier and Huang (2018) further highlight international capital flows to advanced economies as search of safe assets, as the ability to provide safe asset is not uniform across countries. Baele et al. (2020) empirically document FTS episodes for many countries and document the appreciation of safe asset countries' currencies. However, in our paper we restrict the analysis to the case in which only one country is able to provide safe assets, and additionally abstract from exchange rate variations. As a result, the demand for safe assets is not a crucial driver of home bias fluctuations.

Lemma 4 (Constraints for Empirical Relevance). *Under Assumption 3, there exist upper bounds for ρ and ψ, below which the solution to the portfolio problem has the following properties:*

(a) $k_{ii} = k_{jj} \geq k_{ij} = k_{ji} \geq 0$,

(b) $1 - \psi(1-\omega\delta)r^f w_i = 1 - \psi(1-\omega\delta)r^f w_j \geq 0$.

The equalities in both statements of Lemma 4 arise from Assumption 3 on symmetry. Statement (a) captures the stylized fact that for the vast majority of countries, domestic bank lending exceeds cross-border lending. Additionally, both lending positions are bounded away from zero, i.e. we abstract from short selling opportunities. Moreover, statement (b) is a necessary condition for expected bank profitability to be positive, i.e. banks are not exposed to bankruptcy.

Lastly, in order to capture banks' lending preference, we define the *Bank Home Bias Index*.

Definition of Bank Home Bias The countries are indicated by $i \in I$. Denote by d_i the domestic asset holdings of country i's banks, and c_i the cross-border asset holdings. Suppose the home country is country i^*. To compute the benchmark portfolio for country i^*, we first need to compute the total investment to countries that are foreign to country i^*, which equals $\Sigma_{i\neq i^*} d_i + \Sigma_{i\neq i^*}(c_i - c_i^{i^*}) + c_{i^*}$. The first term denotes all the other countries' domestic investments. The second term is all the other countries' cross-border investment, net of the investment that goes to the country i^*. Finally, the third term is the cross-border investment of the home country i^*. The world's total investment is given by $\Sigma_{i\in I}(c_i + d_i)$. Based on this definition, the formula for bank home bias is given by:

$$\mathcal{HB}_{i^*} \equiv 1 - \frac{\text{portfolio foreign share of } i^*}{\text{world portfolio foreign share of } i^*} = 1 - \frac{\frac{c_{i^*}}{c_{i^*}+d_{i^*}}}{\frac{\Sigma_{i\neq i^*} d_i + \Sigma_{i\neq i^*}(c_i - c_i^{i^*}) + c_{i^*}}{\Sigma_i (c_i + d_i)}} \,. \tag{2.2.7}$$

Based on the previous assumptions, we are ready to present the key theoretical result of this section in Proposition 2. We graphically illustrate Proposition 2 in Figure 2.2.

Proposition 2 (Bank Home Bias and Monetary Policy). *Denote $\delta = \frac{d_i}{w_i}$ as the deposit to asset ratio, ω the mark-down on deposit rate that captures the pass-through of risk-free rate to deposit rate, and w the amount of banks' total loanable wealth. Under Assumptions 2 and 3, the following results hold:*

1. *If* $\omega = \delta^{-1}$*, monetary policy tightening unambiguously increases bank home bias.*[9]

2. *If* $\omega < \delta^{-1}$*, there exists a unique value* $\tilde{w}^*$ *which defines a separating line* $\omega^N(w_i)$ *in the* (w_i, ω) *space*

$$\omega^N(w_i) = \frac{1}{\delta}\left(1 - \frac{\tilde{w}_i^*}{w}\right) .$$

   (a) *If* $\omega > \omega^N(w)$*, i.e.* $(1 - \omega\delta)w < \tilde{w}^*$*, monetary policy tightening raises bank home bias.*

   (b) *If* $\omega < \omega^N(w)$*, i.e.* $(1 - \omega\delta)w > \tilde{w}^*$*, monetary policy tightening reduces bank home bias.*

   (c) *On this line, monetary policy does not affect home bias.*

Proposition 2 summaries the state-dependence nature of the impact of monetary policy on bank home bias. Statement (a) depicts a special extreme case, in which the pass-through elasticity from the monetary policy to the deposit rate equals the inverse leverage ratio. This yield the results that the risk-free increment component of Equation 2.2.1 becomes zero, meaning that taking into consideration the size of the deposit, the bank earns nothing after they repay their depositors if all wealth is invested in risk-free assets. This is an upper bound for the deposit rate pass-through, because once ω exceeds this level, bank capital will be eroded. As a consequence, optimal domestic and cross border portfolio holdings will be independent of banks' total balance sheet size w. This implies that cross border lending necessarily decreases in response to a monetary policy tightening. Additionally, as domestic bank lending is less negatively affected by the aforementioned change in monetary policy, bank home bias increases.

Statement (b) characterizes a more general case, in which the pass-through elasticity from monetary policy to the deposit rate is strictly smaller than the inverse leverage ratio. Two regimes of bank home bias regimes emerge under this scenario: (i) a *normal regime* in which a monetary policy tightening increases bank home bias, and (ii) a *reversal regime* in which a monetary policy tightening decreases bank home bias. As it can be seen from Figure 2.2, the latter regime is more likely to arise when the deposit rate elasticity ω is low, which is the case if the monetary policy rate is close to the ZLB. In addition, for a given deposit elasticity ω, shifting from the normal to the reversal regime is more likely if banks dispose a higher amount of loanable wealth w. The reasoning for this is as follows: if the banking sector disposes over a sufficient amount of loanable wealth, a tightening in monetary policy has

[9] If we allow for cross country heterogeneity in fundamental parameters instead of assuming Assumption 3, a sufficient condition for home bias to increase would be given by $\rho \frac{\sigma_j}{\sigma_i} < 1$.

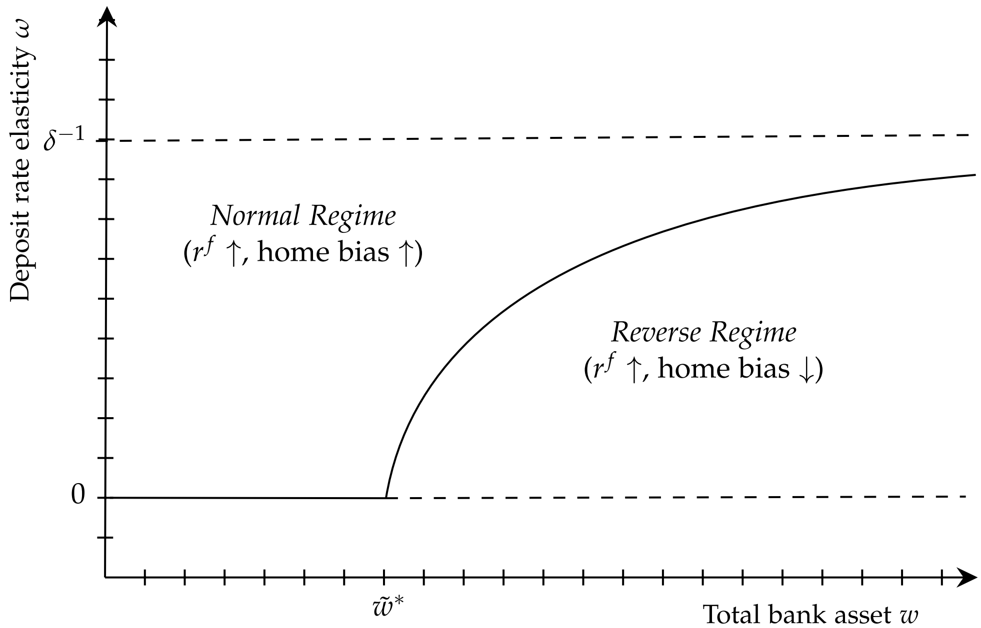

Figure 2.2: Graphical Illustration of bank home bias regimes according to Proposition 2.

according to Corollary 1 ambivalent effects on expected bank profitability. The mechanical effect, i.e. the effect on profitability when keeping the portfolio composition unchanged in response to a policy change, increases the profit margin arising from risk-free rate arbitrage and respectively decreases the profit margin on risky asset holdings. If the former channel is sufficiently strong, i.e. ω sufficiently low, a monetary policy tightening increases expected profitability, which in turn induced larger uncertainty management activities. This leads to a relatively stronger increase in cross-border lending activities compared to domestic lending activities, which in turn suppresses bank home bias. If, however, disposable wealth is rather small, i.e. $w < w^*$, a monetary policy tightening decreases bank profitability at the ZLB, such that cross-border lending decreases and home bias goes up.

Based on Proposition 2, our model has the following predictions on the interplay between cross sectional heterogeneity of the banking sector and bank home bias fluctuations as a reaction to a change in monetary policy.

Corollary 4 (Testable Predictions)**.** *Under the same set of assumptions as in Proposition 2, the following statements hold:*

(a) For a given deposit rate elasticity ω, banks with larger balance sheet w are more likely to decrease

their home bias in response to a monetary policy tightening.

(b) *Banks with larger leverage ratio δ are less likely to decrease their home bias in response to a monetary policy tightening.*

The proof of Corollary 5 is straightforward. Statement (a) follows as ω^N is an increasing function of w, whereas statement (b) follows as ω^N is a decreasing function of δ. Statement (a) of Corollary 5 highlights the role of large globally operating banks in driving recent empirical home bias trends. The larger the balance sheet of banks are, the more likely they are to decrease home bias in response to a monetary policy tightening. As a consequence, the cross-sectional size distribution of banks within an economy turns out to be a crucial driver of aggregate bank home bias fluctuations. In other words, merging and acquisition among banks that affect the banking sector size distribution may have an impact on international lending decisions. Furthermore, a larger leverage ratio shrinks the size of the *ZLB region* as it puts downward pressure on the expected bank profitability in reaction to a monetary policy tightening. To improve financial stability, regulators have recently implemented tighter leverage ratio requirements pushing down the leverage ratio δ. In the light of our theoretical results, such a policy induce in fact a higher likelihood for expansionary monetary policy close to the zero lower bound to increase bank home bias.

Before concluding on this section, we provide a sensitivity analysis on the predictions of Proposition 2 by removing step by step the key frictions of our model. This allows to assess the contribution of each friction in driving bank home bias fluctuations.

Corollary 5 (Frictional Decomposition of Home Bias-Monetary Policy Interaction)**.** *Assume that $\frac{k_{jj}}{k_{ij}} > -1$. Then, under Assumption 2 the following statements hold.*

(a) *Removal Expected Profitability Friction: If $\psi = 0$, i.e. banks' uncertainty management activities do no longer depend on expected profitability, home bias increases in the ratio of banks loanable wealth $\frac{w_i}{w_j}$. Furthermore, a monetary policy tightening (weakly) increases home bias if $\rho \in \left[\underline{\rho}^{NF}, \overline{\rho}^{NF}\right]$, where the correlation bounds are given by*

$$\underline{\rho}^{NF} = -\frac{\zeta_i}{\zeta_j}\frac{\sigma_i}{\sigma_j}\,, \quad \text{and} \quad \overline{\rho}^{NF} = \frac{\sigma_i}{\sigma_j}\,. \tag{2.2.8}$$

If additionally the symmetry Assumption 3 is imposed, the bounds cover the entire support of ρ, such that a monetary tightening unambigously increases bank home bias. Lastly, home bias increases in the size of cross-border information frictions σ_ϵ^2, in the inverse uncertainty *management ability ζ, and in the fundamental correlation of assets if the net risk premium on cross border asset holdings is positive.*

(b) *Removal Cross-Border Information Friction: If $\sigma_\epsilon^2 = 0$, a monetary policy tightening does not affect home bias. In this case, home bias is solely driven by the ratio of loanable wealth. If we additionally impose the symmetry Assumption 3, home bias is always zero.*

The first statement of Corollary 5 provides the benchmark level of home bias when removing the expected profitability friction on bank lending. Home bias depends in this case on the fundamental productivity processes, cross-border uncertainty, uncertainty management abilities, initial wealth and monetary policy. A monetary policy tightening increases home bias in this case if the fundamental correlation among assets lies within a certain range. Additionally, home bias is increases in the size of the domestic balance sheet sector, and decreases in the size of the counterparty banking sector. Finally, the inverse managing ability of banks as well as cross-border information frictions drive up home bias.

When removing the cross border information friction, both countries invest the same amount into country j, such that home bias in turn solely depends on the ratio of foreign to domestic loanable wealth. In case both countries are additionally symmetric in term of their fundamental model parameters, home bias is equal to zero and is therefore insensitive to monetary policy. This decomposition exercise shows that cross-border information frictions are key in generating sizable fluctuations of bank home bias. In contrast, the expected profitability friction, arising through asymmetric interest pass-through in response to monetary policy changes, acts as an amplifier of the information friction in cross-border lending, and as an amplifier or stabilizer of domestic lending depending on the generalized correlation structure.

2.2.6 Further Discussion

Reversal Interest Rate Interpretation

The reversal interest rate concept proposed by Brunnermeier and Koby (2018) defines an effective lower bound on the monetary policy rate, below which accommodative monetary policy has a contractionary effect on bank lending. While the reversal rate is originally applied to the analysis of a closed economy, in a two country open economy setup, a sufficient (not necessary) condition for bank home bias to increase in interest rate cut is that there exist two reversal rates, or a *reversal rate corridor*. The first rate is domestic lending reversal rate, denoted as rr^d, and the other is that of foreign lending, denoted as rr^f, as illustrated in Figure 2.3.

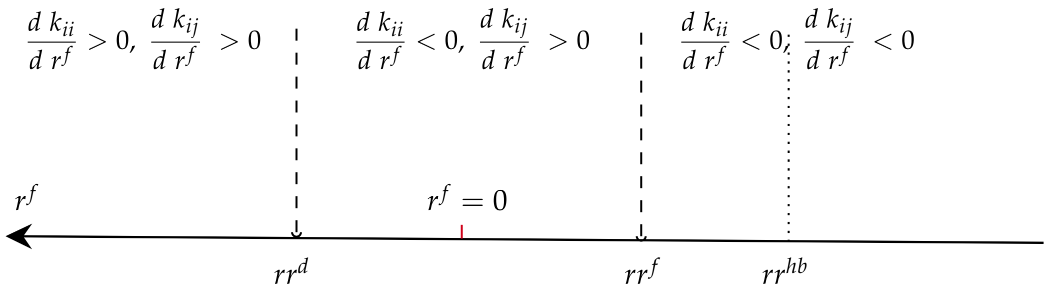

Figure 2.3: Graphical Illustration of Reversal Rates.

As can be seen from the figure, if the reversal rate corridor exists, i.e. $rr^d < rr^f$ is satisfied, then if the risk-free rate falls into this region, i.e. $r^f \in [rr^d, rr^f]$, a further cut on the risk-free rate would stimulate domestic lending but surppress foreign lending, causing a *composition effect* in bank's asset allocation. This substitution from foreign lending to domestic lending can happen without significant changes in the total quantity of credit supplied by the bank. Our model thus points out a novel consequence of the reversal rate concept: it does not only affect the quantity of credit, but also its composition across countries. Note that if this is the case, the reversal rate for bank home bias, denoted as rr^{hb}, would lie even further to the right of the foreign lending reversal rate rr^f.

The existence of the reversal rate corridor depends on the fundamental parameters of the model. First of all, if there is no endogenous cost reduction, i.e. $\psi = 0$, both domestic and foreign lending will depend linearly on the risk-free rate. In this case, there is no reversal rate in the sense that the impact of the interest rate on lending quantity does not vary with the level of the interest rates. This is intuitive, considering the fact that in this case banks' liability side, in particular the deposit, are completely disconnected from the asset side. Therefore, banks' investment decision is independent of its cost of funding.

When $\psi \neq 0$, i.e. management cost depends on future profits, the liability and asset side of bank's balance sheet are no longer independent, and the bank needs to take into consideration the deposit quantity and price when making investment decisions. Unlike Brunnermeier and Koby (2016), our link here in this model is not generated by an exogenous regulatory constraint; rather, it is the *endogenous* response of banks when facing market conditions that values future profits as collateral. Therefore, our results suggest that the regulation on risk weighted capital requirement maybe not the only factor contributing to the existence of reversal rate. The reversal rate for domestic and foreign lending is not straightforward, as the three aforementioned channels introduced by $\psi \neq 0$ all contribute to the effect of monetary policy rate. To decompose the effect, we refer to the difference in pledgeablity assumption in Corollary 3. We can see that if $\kappa_d = \kappa_f = 0$, i.e. the only pledgeable asset is risk-free return, the effect of risk-free rate on portfolio holding is still linear. If we further introduce generalized correlation structure by assuming $\kappa_d \neq 0$, there is possibility for a reversal rate, as the quantity of investment is now a non-linear function in r^f. As a reduction in risk-free rate decreases the generalized correlation $\tilde{\rho}$, this could lead to less investment in foreign asset and more investment in domestic asset, provided the uncertainty friction on foreign asset is large enough, thereby gives rise to the reversal rate corridor. Furthermore, if we introduce instead the variance reduction channel of foreign asset, i.e. $\kappa_f \neq 0$, the policy function also becomes non-linear in r^f, due to the fact that the reduction in risk-free rate leads to an strengthening of the variance channel and boost investment in foreign asset. In this case, the existence of reversal rate corridor depends on the underlying correlation of the fundamentals.

Bank-equity Home Bias Disparity.

In section 2.4, we have documented empirical evidence that equity home bias and bank home fluctuations have stopped to comove in the aftermath of the Great Recession. Specifically, as bank home bias sharply and permanently increases, equity home bias continues to fall. Our model is able to reconcile and shed light on the mechanism behind these findings. Whereas both banks and equity investors face cross border information frictions, the profitability channel is unique to the banking sector and key to reconcile this puzzle. In the case of symmetric model parameters, an expansionary monetary policy increases bank home bias at the ZLB according to Proposition 2. On the contrary, when removing the expected profitability friction on the bank lending channel, our model environment can be reinterpreted as the portfolio choice of equity investors. In this case, expansionary monetary policy decreases equity home bias according to Corollary 5. As a consequence, our model demonstrates that a low interest rate environment has vastly different implications for bank and equity investment decisions. The former faces tighter financing constraints due to asymmetric interest rate pass-through, while the latter is unaffected by or benefits from long lasting low interest rate episodes.

2.3 Quantitataive Model

In this section, we develop a dynamic general equilibrium incomplete market extension of the of banking in 2.2, and then we adapt it in into a full-blown macro environment. Incorporating the dynamic decision allows us to understand the impact of endogenous uncertainty management under dynamic consumption saving decisions with precautionary saving motives due to market incompleteness. In the context of banking, precautionary saving of agents would be the bank's hoarding of safe assets, which is one important phenomenon in the post-crisis era. In addition, with an additional deposit supply function, we endogenize the deposit quantity and can examine the general equilibrium effect of the policy rate change on bank lending via deposit quantity changes. In this case, the pass-through parameter alone cannot determine the deposit quantity; Rather, the shape of the supply of deposits affects the equilibrium interest rate. Finally, the extension into a macro model is to provide quantitative assessment of the macroeconomic effects of the geographical reallocation of banks' credit supply in an open economy, following an adjustment to the monetary policy rate.

2.3.1 Setup

Dynamic Bank Problem

In the dynamic model, the representative bank decides at each period how much dividends π_t to pay to their equity holders to maximize their discounted sum of utility and how to allocate the rest of the funds into different assets. Essentially, the problem can be broken down into two parts: a consumption saving problem with an incomplete market, and a portfolio allocation problem with endogenous uncertainty management. The portfolio problem is the same as in the static model [10], thus we omit the interim stage computation and directly use the results in the first stage, where the bank's maximization objective is given by

[10] Note that in the dynamic problem $e_{i,t}$ is cum dividend equity at period t, and $e_{i,t} - \pi_{i,t}$ is ex-dividend equity at period t. To keep the interim stage management analysis simple and consistent with the static model, we define the profitability in a *cum dividend* sense, i.e. the profitability at period t contains the dividend payment as if it can be reinvested into a risk-free asset.

$$
\begin{aligned}
V_t(e_{i,t}) \equiv & \max_{\{\pi_{i,t}, k_{ii,t+1}, k_{ij,t+1}, b_{i,t}\}} u(\pi_{i,t}) + \beta \mathbb{E}_t V_{t+1}(e_{i,t+1}) \\
s.t. \quad d_{i,t} &= \frac{\delta}{1-\delta} e_{i,t} \ , \\
w_{i,t} &= d_{i,t} + e_{i,t} \ , \\
w_{i,t} &= \pi_{i,t} + (1+\tau)\left(k_{ii,t+1} + k_{ij,t+1}\right) + b_{i,t} \ , \\
e_{i,t+1} &= R^l_{ii,t+1} k_{ii,t+1} + \boldsymbol{R^l_{ij,t+1}} k_{ij,t+1} + R^f_t b_{i,t} - R^d_t d_{i,t} \ ,
\end{aligned}
$$

where $\boldsymbol{R_{ij,t+1}}$ is the post-management risky return on foreign lending, and $\pi_{i,t}$ denotes bankers' dividend stream which they return to their household family income. Note that here we do not allow the bank to choose the deposit quantity; rather, we assume that the bank always leveraged up to the maximum leverage ratio allowed, which is pinned down by the deposit to asset ratio δ. This is to simplify the optimal liability side structure problem, as our analysis is mainly on the asset allocation side. The assumption is not completely innocuous. However, in reality, the leverage ratio constraint serves as a binding requirement for most banks, it is not too costly for our analysis to be relevant. Additionally, τ resembles a regulatory wedge which can be interpreted as a risk-weighted capital requirement if positive.

This setup is based on the incomplete market model of Angeletos and Calvet (2006) but differs in three major ways. First of all, the state variable of the value function is equity, as opposed to the total wealth of households in Angeletos and Calvet (2006), since the high leverage ratio is the the bank's most significant feature. As a result, when making investment decisions, the household only considers their current period financial and non-financial income, whereas the bank also takes into consideration the current period deposit income, which acts as an amplifier to any change to the equity. The investment activities of the bank might also be subject to a series of restrictions, captured by the additional cost term τ. Second, Angeletos and Calvet (2006) has only one productive asset, whereas we have an open economy setup with two productive assets, one for the domestic country and one for the foreign. In Angeletos and Calvet (2006), the authors discuss an extension by adding a market of risky financial assets. The assets, however, are solely used as a hedging tool as they are assumed to be in zero net supply with no risk premia. Thus, the risky assets play a role in the precautionary saving decision only by affecting the *ex-post* definition of shock variance. Our setup is similar to this extension in the sense that in addition to the domestic asset (productive capital), there exists another risky asset, i.e. foreign asset, that can be used to hedge market incompleteness. However, this asset is not in zero net supply, and the variance is no longer exogenous, as we allow the agents to pay a cost to reduce the uncertainty variance. It can be reduced by diversification or management with a pecuniary cost. As a result, although the market is incomplete in our model, the variance of the portfolio is *endogenous*. This allows the bank to have more dynamic trade-off opportunities when facing market incompleteness, in addition to precautionary saving.

To close the model, we introduce an ad hoc form of deposit supply equation in this economy, given by

$$d = (1 + \Theta_d \log\left(R_t^d\right))\bar{d} \; ,$$

where $(\Theta_d, \bar{d})$ are two parameters governing the sensitivity of deposit quantity with respect to the deposit rate. The idea of having one deposit supply function to close the general equilibrium is the same as Bianchi and Bigio (2022). In the next section, we provide a microfoundation of the deposit supply function with a household and production sector.

Rest of the economy

The economy consists of global banks and three additional sectors, namely households, intermediary production firms (I.Firms), and final retail firms (F firms). Households and production firms constitute the real economy, as households supply deposits and firms demand bank loans to produce. On top of the real economy, adding retail firms introduces nominal prices and interests. This allows us to perform several policy analyses, including both monetary and regulatory policies. We abstract from international trade since it is not the primary mechanism of our research. The structure of the foreign country is the same as the domestic one, so we omit to show the rest of the economy in the figure except their banking sector and intermediate firms. For simplicity, we drop the notation i and j and instead denote foreign variables with a star. Figure 2.16 in Appendix 2.7.2 gives an illustration of the economy structure.

Banks in this economy face the same problem as in the dynamic model. Taking deposit rate, leverage ratio, risk-free return, and risky project returns as given, they choose their investment in domestic and foreign production sectors as well as a risk-free asset. Since we assume the two countries are perfectly symmetric, the investment of domestic bank into foreign firms *equals* the investment of foreign bank into domestic firm, i.e. $L_{f,t} = L^*_{f,t}$. Therefore, the total lending of banks equals to the total credit the domestic production firms receive, $L_t = L_{d,t} + L^*_{f,t} = L_{d,t} + L_{f,t}$.

Households Households have the following utility function

$$\mathcal{U}(C_t, L_t) = \frac{C_t^{1-\sigma}}{1-\sigma} + \chi \frac{L_t^{1-\varphi}}{1-\varphi} ,$$
$$L_t = 1 - N_t .$$

Given the final good price P_t, which is determined by the final retail firm, the households face the following optimization problem

$$\max_{C_t, N_t, D_t, K_{t+1}} \sum_{t=0}^{\infty} \beta^t \mathcal{U}(C_t, N_t)$$
$$\text{s.t.} \quad D_{t+1} + K_{t+1} \leq \frac{W_t}{P_t} N_t + R_t^k K_t + R_t^d \frac{P_t}{P_{t-1}} D_t + \frac{\Pi_t}{P_t} ,$$
$$C_t \leq R_{t+1}^d \frac{P_{t+1}}{P_t} D_{t+1} \theta_d .$$

As can be seen from the setup, households gain utility from consuming goods C_t and leisure L_t. Their income consists of two parts: labor income and investment income. Labor income is pinned down by the hours worked, $N_t = 1 - L_t$, and wage level W_t. Investment income can be further decomposed into deposit income $R_t^d D_t$ and capital income $R_t^k K_t$[11]. When choosing the investments, the households need to take into consideration another constraint, which is a deposit-in-advance constraint. This captures the fact that deposits have an advantage of higher liquidity over capital investment and are thus used for consumption goods purchases. θ_d characterizes this liquidity effect of deposit.

Production firms Production firms uses labor and capital to produce. The production technology is standard Cobb-Douglas, with productivity A_t.

$$Y_t = A_t K_t^{\alpha} N_t^{1-\alpha}.$$

The productivity consists of two components, $A_t = \bar{A} a_t$. The first component, $\bar{A}_t$, is the deterministic part of the productivity and is known to all agents in the economy. The second component, a_t, is a stochastic TFP shock with mean larger than one. The distribution of a_t is known, but the realization is only observable at period t.

Furthermore, we assume the firms are *financially constrained*, in the sense that the expendi-

[11] To keep the notation simple, we use R_t^k and R_t^d to denote real returns.

ture on the factor input at period t need to be prepaid at period $t-1$ before the production is carried out. To finance these purchases, firms obtain loans from the domestic bank and the foreign bank with a *risk-shifting* contract: Banks grant loans to firms before production to help pay the factor expenditure, in exchange for the additional quantity of production coming from the stochastic component of the productivity, as a risky return to the loan. As a result, intermediate firms solve the following problem

$$\begin{aligned}\max_{K_t,N_t} \pi =& P_{I,t}\bar{Y}_t - R^k_t K_t - W_t N_t \\ \text{s.t.} \quad \bar{Y}_t =& \bar{A} K_t^{\alpha} N_t^{1-\alpha} \\ L_t \geq & R^k_t K_t + \frac{W_t}{P_t} N_t \;.\;,\end{aligned}$$

where $L_t = L_{d,t} + L^*_{f,t}$ is the total loans obtained from domestic and foreign bank.

The price $P_{I,t}$ is now interpreted as the *relative* price of intermediate good to final good, and that the liquidity constraint for the firm is now denoted using real wage. After factor input decisions have been made, stochastic component of the TFP is realized, and production is carried out. Final output is thus given by $Y_t = a_t \bar{Y}_t$. Firms pay gross return $R_t = a_t$ on the loan [12]. For the production sector, the only novel parameter that we need to specify is λ_d, the deposit liquidity parameter on the deposit-in-advance constraint. We choose the value to be 0.25, which pins down in equilibrium a liquid asset ratio that is consistent with the observations.

Retail firms The retail sector consists of a continuum of mass unity of retail firms, which work in the same way as the final retail firm in Gertler and Karadi (2011). Each retailer purchases intermediate goods as the sole input, repack them into final goods $Y_{f,t}$, and sell them at price $P_{f,t}$ to households who consume these goods with a CES aggregator

$$Y_t = \left[\int_0^1 Y_{f,t}^{(\varepsilon-1)/\varepsilon} df\right]^{\varepsilon/(\varepsilon-1)} \;.$$

[12]Since $Y_t = (1+\lambda_t^f)(R^k_t K_t + W_t N_t) = (1+\lambda^f_t)L_t$, we have $a_t \bar{Y}_t \geq R_t L_t$. That is, firms would never *default* on the loans, while the return on the loans is still risky. This assumption thus helps keep the loan risks *exogenous* without contamination by endogenous risks such as defaults due to production decisions. As $\lambda_t > 0$, firms make profits. We assume profits are redistributed back to households.

The demand faced by each retail firm is thus given by

$$Y_{f,t} = \left(\frac{P_{f,t}}{P_t}\right)^{-\varepsilon} Y_t \ , \quad \text{where} \quad P_t = \left[\int_0^1 P_{f,t}^{1-\varepsilon} df\right]^{1/(1-\varepsilon)} \ .$$

Retailers are subject to Rotemberg price adjustment costs. They choose $P_{f,t}$ to solve the maximization problem given by

$$\max_{P_{f,t+j}} E_t \sum_{j=0}^{\infty} \beta^j \Lambda_{t,t+j} \left(\left(\frac{P_{f,t+j}}{P_{t+j}} - P_{I,t+j} \right) Y_{f,t+j} - \frac{\phi}{2} \left(\frac{P_{f,t+j}}{P_{f,t+j-1}} - 1 \right)^2 Y_{t+j} \right)$$

where $P_{I,t}$ is the real cost of final good production, which is just intermediate good price relative to the final good, i.e. $P_{I,t} = 1/P_t$. In a symmetric equilibrium, all firms choose the same price, $P^*_{f,t} = P^*_t = P_t$. The condition becomes:

$$\phi \left(\frac{P_t}{P_{t-1}} - 1 \right) \frac{P_t}{P_{t-1}} = \phi E_t \beta \Lambda_{t,t+1} \left(\frac{P_{t+1}}{P_t} - 1 \right) \frac{P_{t+1}}{P_t} \frac{Y_{t+1}}{Y_t} + 1 - \varepsilon + \varepsilon P_{I,t}$$

Monetary Authority

We assume that real rate R_t^f and nominal rate i_t is linked by the following Fisher equation

$$1 + i_t = R_{t+1} \frac{E_t P_{t+1}}{P_t} \ .$$

The monetary authroity implement the following interest rate rule

$$\log(1 + i_t) = \rho_i \log(1 + i_{t-1}) + (1 - \rho_i) \log(R^*) + (1 - \rho_i) \phi_\pi \log(\pi_t) + \varepsilon_t$$

where $\pi_t = P_t/P_{t-1}$ is the gross inflation rate and R^* is the steady state real rate that needs also to be consistent with equilibrium real return on the safe asset in bank's problem.

2.3.2 Solution Concept

The solution concept of this model is to find a deterministic equilibrium à la Angeletos and Calvet (2006), which allows us to keep the dynamic portfolio problem solution tractable with all the features of our static model. The definition below characterizes a *deterministic equilibrium*, in which a representative bank perfectly anticipates the sequence of risk-free monetary policy rates $\{R^f\}_{t \in [1,\infty)}$ set by the central bank. The equilibrium can be solved using the guess-and-verify approach.

Equilibrium Definition

We define the equilibrium in the model in à la Angeletos and Calvet (2005), with one key modification. In Angeletos and Calvet (2005), the authors assume a form of value function that is linear in wealth, consistent with the optimal portfolio solution under a constant absolute risk aversion structure. That is, the optimal asset allocation is independent of wealth. However, under our setup, due to the endogeneity of the riskiness in foreign investment, the wealth effect is reintroduced into the portfolio problem. The optimal portfolio solution depends on the wealth effect on the portfolio solution. As a result, the optimal portfolio solution becomes linearly dependent on wealth, and the variance is thus quadratic in wealth.

Therefore, to keep the tractability of the portfolio solution, we impose an additional assumption that the banks are *bounded rational* when choosing the dividends and investments, in the sense that they only care about the first-order component of the wealth on the value function and ignore the role of wealth in the portfolio variance. Therefore, the banks are *myopic* when forming their expectations, and they are aware that all the banks in the banking sector are myopic in the same way. The value function of the bank then becomes

$$V_t(e_{i,t}) \equiv \max_{\{\pi_{i,t},k_{ii,t+1},k_{ij,t+1},b_{i,t}\}} u(\pi_{i,t}) + \beta \mathbb{E}_t^b V_{t+1}(e_{i,t+1})$$

where $\mathbb{E}^b$ denotes the bounded rational expectation where the banks omit the impact of wealth on portfolio variance. Under this assumption, the model admits the following equilibrium.

Definition 1 (Equilibrium Concept). *An incomplete markets equilibrium consists of a collection of state-contingent plans* $\{\pi_{i,t}, k_{ii,t+1}, k_{ij,t+1}, b_{i,t}, d_{i,t}\}_{t=0}^{\infty}$ *such that*

1. $\{\pi_{i,t}, k_{ii,t+1}, k_{ij,t+1}, b_{i,t}\}_{t=0}^{\infty}$ *maximizes the utility of the bankers located in each country* (i,j)*, under the bounded rational expectation.*

2. *the bank are always fully leveraged, i.e.* $d_{i,t+1}/w_{i,t} = \delta$.

3. *bankers have perfect foresight on the sequence* $\{r_t^f\}_{t=0}^{\infty}$.

4. *the central bank allows to hold or borrow reserves given* r_t^f *arbitrarily.*

5. *deposit market clears at deposit rate* $R_t^d = \omega r_t^f + 1$.

Bank Portfolio Solution

The problem can be solved in the same manner as Angeletos and Calvet (2006), using the property of the CARA-Normal framework. We solve the model by the method of undetermined coefficient with a linear guess on the policy functions

$$V_t(w_{it}) = u(\gamma_{i,t} w_{i,t} + \eta_{i,t}) \ , \quad \pi_{i,t} = \hat{\gamma}_{i,t} w_{i,t} + \hat{\eta}_{i,t} \ ,$$

where $\gamma_{i,t}, \hat{\gamma}_{i,t} \in \mathbb{R}_+$ and $\eta_{i,t}, \hat{\eta}_{i,t} \in \mathbb{R}$ are non-random coefficients to be pinned down.

Similar to the static model, we can define a series of augmented parameters for ease of notation

$$\begin{aligned}
\tilde{\sigma}_\epsilon^2 &= \sigma_\epsilon^2 \left[1 - \psi(1-\omega\delta) w_{i,t}(R_t^f - 1)\right] \ , \\
\tilde{\sigma}_j^2 &= \sigma_j^2 - \kappa_f \zeta_i \psi \theta (\mu_{j,t+1} - (1+\frac{\tau}{\theta}) R_t^f) \sigma_\epsilon^2 \ , \\
\tilde{\rho} &= \frac{\left(\rho\sigma_i\sigma_j - \frac{\kappa_d}{2}\zeta_i\psi\theta(\mu_{i,t+1} - (1+\frac{\tau}{\theta})R_t^f)\sigma_\epsilon^2\right)}{\sigma_i\tilde{\sigma}_j} \ .
\end{aligned}$$

Given the linear guess on the value function and the consumption rule, we can solve the solution to the dynamic portfolio problem. By comparing coefficients, we can then pin down the form of the guessed parameter. The key results is shown in Proposition 3.

Proposition 3 (Dynamic Portfolio choice)**.** *The dynamic portfolio choice is given by*

$$\begin{aligned}
k_{ii,t+1} &= \frac{1}{1-\tilde{\rho}^2} \left[\frac{\mu_i - (1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i^2} - \tilde{\rho} \frac{\mu_j - (1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i\tilde{\sigma}_j} + \frac{1}{2}\tilde{\rho}\frac{\zeta_i\tilde{\sigma}_\epsilon^2}{\sigma_i\tilde{\sigma}_j} \right] \ , \\
k_{ij,t+1} &= \frac{1}{1-\tilde{\rho}^2} \left[\frac{\mu_j - (1+\tau)R_t^f}{\alpha\gamma_{t+1}\tilde{\sigma}_j^2} - \tilde{\rho} \frac{\mu_i - (1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i\tilde{\sigma}_j} - \frac{1}{2}\frac{\zeta_i\tilde{\sigma}_\epsilon^2}{\alpha\tilde{\sigma}_j^2} \right] \ , \\
b &= (1-\gamma_t) w_{i,t} - \eta_t + \frac{1}{\alpha}\ln\gamma_t - (1+\tau)k_{ii,t+1} - (1+\tau)k_{ij,t+1}.
\end{aligned}$$

And the effective risk aversion parameter is given by

$$\gamma_t = \gamma_{t+1} R_t^f \left[1 - \mathcal{A}(R_t^f - 1) - \gamma_t\right]$$

where

$$\mathcal{A} = -(1+\tau)\frac{1}{1-\tilde{\rho}^2}\frac{1}{2}\left(\frac{\tilde{\rho}\zeta_i}{\alpha\sigma_i\tilde{\sigma}_j} - \frac{\zeta_i}{\alpha\tilde{\sigma}_j^2}\right)\sigma_\epsilon^2\psi(1-\omega\delta)$$

Note that the variable γ_t shows up in the expression of the optimal portfolio policy function. This captures the impact of the policy rate on the *effective risk aversion* of the bank. Without the uncertainty term σ_ϵ^2, the expression of γ_t collapses back to that in the Angeletos and Calvet (2006). The fact that this variable, being a function of the risk-free rate, illustrates how market incompleteness generates a novel channel through which policy rate change affects investment decisions, namely the endogenous risk premia channel. This channel, highlighted in Angeletos and Calvet (2006), shows that if the policy rate has an anticipated increase in future periods, the agents in the economy would become less willing to invest in the risky asset, as captured by an increase in the variable γ_t.

However, in our model, the impact of the anticipated interest rate increase is no longer monotone, as can be seen from the expression. The presence of uncertainty leads to a non-zero parameter $\mathcal{A}$, which in turn brings in a second order term of R_t^f. This is because the costly management of uncertainty reintroduced the wealth effect into the portfolio choices of the bank. Moreover, since the bank's expected wealth has an impact on the riskiness of the project in the current period, the monetary policy rate would impact the potential changes in profit through the rate spread between the risk-free rate and deposit rate.

Parameterization

The model parameterization consists of two parts: Banking sector parameters, as shown in Table 2.1, and conventional parameters that characterize the rest of the economy, as shown in Table 2.4.

Table 2.1 lists the choice of parameter values used for the banking sector. We run the dynamic bank model under this parameterization and compare the key statistics generated by the model with that of the U.S. banking sector. The model is close to the literature or the data observed. The equity-to-asset ratio, which is 20 %, and the net risky loan returns of both domestic and foreign projects, which are 3 %, are the parameters we pick, and they are close to that of the values in Brunnermeier and Koby (2018). In our baseline calibration, we have a steady state loan-to-asset ratio of 69.3%, and a bank dividend ratio of 9.6%, defined as the dividend payment divided by equity. The numbers are respectively 60 %, and 11.4% in Brunnermeier and Koby (2018)[13]. Lastly, the home bias generated by the model ranges from 0.60 to 0.74 as we modify the profitability channel parameter ψ, which is roughly close to

[13]Note that in Brunnermeier and Koby (2018), bank assets consist of loans and fixed-income securities, and in our case, fixed-income securities are just a single risk-free asset

the 0.70 lowest points of the U.S. but is relatively close. The steady-state policy rate in this incomplete market economy is given by 0.87% and the equilibrium deposit rate 0.52%.

Table 2.2 gives the parameterization of the rest of the economy. We adopt the conventional values used in the literature for these parameters to keep consistency.

2.3.3 Dynamic Bank Home Bias

To start with, we parameterize the model to illustrate the bank home bias variations in our dynamic bank problem, using the ad hoc deposit supply function.

Baseline

In this baseline parameterization, we specify the pledgeability parameters κ_d and κ_f to be zero, which means that the risky component of the profits, as shown in Equation 2.7.1, does not affect the uncertainty management cost. This is equivalent to saying that only the risk-free part of the future profit can be used to decrease management cost. As a result, out of the three new channels brought about by the profitability channel, namely the attenuation of uncertainty friction channel, variance reduction channel, and generalized correlation structure channel, only the first one is presence in our baseline parameterization. The steady state values generated by the baseline parameterization is given in Table 2.3.

We start with numerical experiments to illustrate key the properties of the model, i.e. to what extent the profitability channel of monetary policy translate into a higher degree of home bias following an interest rate cut.

In the first experiment, we generate a 50 basis point monetary policy shock at second period. This exogenous shock decreases the policy rate R^f and has three implications. The first two are the same as that in the static case, i.e. the risk premium effect and profitability effect. The first implies higher investment in risky assets and less in the risk-free asset, as the spread between the return to the two becomes larger. The second one states that a rate cut has a negative impact on bank profitability, as we assume the bank cannot perfectly pass on the rate cut to depositors. This has a detrimental effect on the bank's ability to manage uncertainty, therefore a rate cut tilts the balance between domestic and foreign lending. Moreover, since we are in a dynamic environment, there is a third channel. The risk that the bank face is endogenous as it depends on the bank's investment in risky assets. Therefore, as a rate cut triggers the banks to invest more in the risky asset, it creates also a larger variance for the market incompleteness, thereby increasing the precautionary saving incentive as well.

The shock affects banks profit through both risk-free arbitrage component and risky component. On the one hand, since deposit rate R^d is pinned down by deposit market clearing, and both deposit supply and demand is pre-determined at each period, the deposit rate R_d does not adjust contemporaneously to the shock. Therefore, the policy shock creating a enlarging gap between risk-free rate and deposit rate and a decrease in the risk-free component of bank's profit. On the other hand, the cut in the interest rate implies higher risk-premium in risky loans, leading to a re-balancing of portfolio from risk-free asset to risky loans. Under current parameterization, the increase in profit through risky loans dominates the loss from risk-free arbitrage, thereby increasing the bank's end-of-period equity. Since the bank always leverage up to maximum level allowed, an increase in equity translates into an increase in deposit demand, which causes the slight overshoot of deposit rate R^d and risk-free rate R^f in the next period.

As in the static model, ψ governs the degree to which banks' profitability has an impact has the. By altering ψ, we change the degree to which a bank's profitability matters for the uncertainty management decisions. We find that a higher ψ lead to a lower level of home bias, which is consistent with our assumption that the bank can use profits to lower the cost of uncertainty management. This leads to higher investment in risky assets and higher portfolio variance. However, even with the presence of higher risks, the bank invests less in the risk-free asset, which contradicts the usual precautionary saving motive. This suggests that with a profitability channel, a bank becomes better at managing uncertainty and thus chooses to better manage the risks than using the safe asset to save, even though it results in a riskier portfolio.

For the impulse responses, as can be seen in Figure 2.6, a higher ψ leads to a larger decrease of home bias to rate cut. This also confirms the intuition of the static model, i.e. if banks' profit from the spread between risk-free and deposit return is crucial for the costly management of uncertainty, a rate cut leads to higher bias against the foreign asset, thereby reducing the impact of a rate cut on stimulating lending.

The dynamic feature of the model allows us to analyze not only the impact of contemporaneous policy rate changes on cross-border lending allocation, but also the impact of future changes. Figure 2.7 shows the response of bank home bias following a sequences of rate cut that results in a persistent low interest rate period.

In addition to the level of home bias, we can also examine the impact on the quantity of lending. Following the discussion in previous section on the connection to the reversal rate corridor, Figure 2.8 exhibits how the mechanism of costly uncertainty management can generate reversal rate for foreign lending.

Robustness

To test for the robustness of the results, we alter the key parameters in our model to examine the changes in responses.

Pass-through Elasticity We start by showing the impact of pass-through elasticity ω on the effect of policy rate changes. In the static model in the previous section, the degree to which the bank can pass on a cut in the risk-free asset return is crucial in determining bank profits, which in turn affects the extent to which the bank can manage uncertainty in foreign investment.

In the dynamic model, however, a cut in the risk-free rate does not contemporanously affect deposit rate, as the deposit rate is determined in equilibrium by deposit market clearing. Therefore, pass-through elasticity ω affects only the responses of the risk-free and deposit rates after the period with a policy rate cut.

Leverage Ratio By altering δ, we change to what extent the bank can leverage up using the deposit they collect. We find that the higher δ, the higher the level of home bias. This is due to the profitability channel of the model, as higher leverage means more deposit payment and therefore less profit for the bank. In addition, we find that higher δ lowers the size of bank equity and total asset size under this general equilibrium setup. Dynamically, this leads to more decrease in home bias when there is a rate cut and a higher overshoot when the cut ends. This is consistent with the model because the higher leverage of the bank in our model essentially weakens the negative impact of the profitability channel on bank lending. As more impact of rate cut can be shifted to depositors through a cut in the deposit rate, a higher δ reduces the negative impact of a rate cut on bank profitability. Therefore, it makes the responses of bank home bias more cyclical with rate cuts.

Fundamental Correlation By lowering ρ, we change the correlation between domestic and foreign countries' fundamental TFP shocks. We find that this leads to both a lower level of home bias and lower investment in the risk-free asset. This is intuitive, as lower correlation means higher hedging benefits. Therefore, facing insurable investment risks, the bank would choose to diversify rather than do the precautionary saving. Dynamically, lowering ρ weakens both the decline of home bias to the rate cut and the overshoot of home bias after the rate cut. This is due to the fact that lower correlation means higher complementarity between domestic and foreign asset, thereby it weakens the composition effect of policy rate cut on bank lending.

2.3.4 Monetary Policy Effectiveness

To evaluate how the effect a monetary policy shock can be compromised by the presence of profitability effect on foreign lending, we generate an innovation of 50 basis point to the Taylor rule. We then generate the same shock but vary the degree to which profitability channel matters, by changing the parameter ψ..

Figure 2.9 show the nominal rate path and the impulse responses of home bias, total loan, and output. Note that here the impact of loan is relatively large, this is due to the fact that we adopt the specification in the dynamic model, in which we assume that uncertainty management is perfect for domestic loan. While in a more complete setup, the profitability channel would also be present for domestic loan, albeit to a less extent than that for foreign lending, which would tune down the response of domestic loans.

As can be seen from the figure, the rate cut is accompanied by an re-balancing of the portfolio towards risky assets, as shown by the increase in total loans. Moreover, as in the baseline dynamic model, home bias index captures the re-balancing *within* the category of risky assets. With the profitability channel becoming more significant for uncertainty management, the impact of a rate cut on home bias becomes more positive, as in dynamic model. This translate into a less increase in the total loan.

In the case where the profitability channel is moderate, i.e.$\psi = 2$, the cut in interest rate brings a relative increase in foreign lending relative to domestic lending, which can also be seen from the loan quantity in the Appendix Figure 2.17. However, as ψ becomes higher, the initial drop in the spread between nominal rate and deposit rate induces less effective managing of the foreign investment. The bank start to shift towards domestic lending. The increase in domestic loans, however, is not enough to cover the decrease in foreign lending, leading to a decrease in the total quantity of loans. Given that we assume symmetry between the countries, less foreign investment by domestic banking sector is mirrored as less foreign capital inflow, thereby resulting less lending to domestic firms. Since in our model, production firms' investment is bounded by the rationing of bank loans, less loan quantity directly translates into less output. Our baseline parameterization shows that with ψ increases from 2 to 6, total loans stimulated by the rate cut decreases by almost 10%, resulting in a difference of 0.18% in terms of the output responses.

On the household side, we check the impulse responses of consumption and labor supply. As we vary the parameter ψ, the response in labor is in accordance with that of the output. However, the consumption changes in the opposite manner, i.e. a higher ψ induces higher consumption responses. This inverse pattern of consumption arises from the constraint on consumption imposed by deposit liquidity. As we assume in the model, households pay their consumption via the amount of deposit set aside at the beginning of the periods. Therefore, since lower ψ induces more decrease in deposits in the subsequent period, consumption responds less positively to the simulation.

Finally, we plot the responses of capital and return on capital. They are consistent with the patterns of the other variables. Note that similar to the responses of consumption, in this case a higher ψ also induces less decrease in the aggregate capital.

2.4 Stylized Facts

In this section, we study the variations of bank home bias at the country level to see whether our model's findings are consistent with the empirical patterns observed. We briefly introduce variables used to construct the home bias dataset and the key empirical findings[14].

2.4.1 Data Description

We compute bank home bias at the country level. To achieve this goal, we construct a dataset of global bank lending using data from multiple sources. As a comparison, we also look at the home bias of equity investors and potential driving factors of bank home bias, particularly uncertainty, the key factors we assumed in the model.

Bank We use data from multiple resources to build a global bank lending dataset. For domestic lending, we obtain data from International Monetary Fund (IMF)'s International Financial Statistics (IFS) dataset. The institutions under the classification system would be Other Depository Corporations (ODCs), which, together with central banks, consist of the broader category of Financial Corporations (FCs). For cross-border lending, we turn to Bank for International Settlements' Locational Banking Statistics (LBS). Although the IFS dataset

[14] For further details on the construction of the dataset and empirical studies of bank home bias, the readers are referred to the companion paper entitled *Country-level Bank Home Bias: An Empirical Investigation*.

also provides data on foreign lending, LBS captures around 95% of all cross-border activities from the perspective of residence and gives richer details regarding the characteristics. The definition of banks in LBS is Deposit-taking Corporations, except for the Central Bank.

Equity Besides the banking sector, we also apply the definition of home bias to countries' equity investment portfolios. The key data source used for equity is the Coordinated Portfolio Investment Survey from the IMF, which documents the holdings of foreign equity investment at the country level. Combined with data on domestic equity market capitalization obtained from the World Bank, we construct an annual home bias indicator for equity in the same way as bank home bias.

Uncertainty Uncertainty is the key driver for cross-border decisions in our model. We adopt two measures from the literature to compute our uncertainty index. The first one is the Economic Policy Uncertainty Index (EPU), a comprehensive index of uncertainty based on news, tax code, and survey results developed by Baker et al. (2016). Although this index is available for over a dozen of countries, to ensure that we have the maximum data coverage, we also use the World Uncertainty Index (WUI) developed by Ahir et al. (2018). The dataset provides country-level data every month for over one hundred countries. Using this dataset, we can construct the domestic uncertainty index and foreign uncertainty index for each country.

2.4.2 Stylized Facts

Fact I: Bank home bias To start with, we show the general trend of bank home bias. The red line in Figure 2.12 displays the bank home bias for the United States, and the black line is the weighted world bank home bias. The most salient feature we observe is a V-shaped trend. Before the Great Recession, US banks experienced a steady decrease in bank home bias. After the crisis, however, the trend reversed and returned to its original level in the early 2000s. The weighted world average of bank home bias shows a similar trend. These variations across time suggest that relative preferences for domestic lending are not constant but rather a state-dependent reflection of various underlying economic forces. The persistent period of high home bias during the zero lower bound period is consistent with the simulation of the dynamic bank model, as shown in Figure 2.7.

Fact II: Bank vs. equity home bias Contrasting bank home bias with equity home bias, as shown in Figure 2.13, we see that the weighted world bank home bias and the weighted world equity home bias had similar trends prior to the Great Recession. After the recession, however, the trend continues for equity home bias but reverses for bank home bias. The departure in the trends aligns with the predictions of our model. Since the equity investors are, in general, not leveraged, and their profitability is not affected by the interest rate margin, the low-interest rate periods after the Great Recession did not significantly harm the profit situation. In addition, the wealth of equity investors might enjoy a boost with the appreciation of stock values during the zero lower bound period. Banks, on the contrary, face a shrunk interest rate margin and, thus, tighter profitability conditions. While equity investments benefit from the expansionary monetary policy due to the appreciation of asset prices, bank investments, most of which are loans, are less liquid and often non-tradable. Moreover, due to interest rate pass-through rigidity, they experience a loss in profit if the deposit rate is rigid. As is shown by our model, the differences in profitability constrain the investors' ability to take risks overseas and manage them properly, which then leads to the divergence in bank and equity home bias trends.

Fact III: Bank home bias and uncertainty Lastly, we are interested in the correlation between bank home bias and uncertainty, the key factor that contributes to home bias variation in our model. In Figure 2.14, we plot the weighted average world bank home bias against the weighted average Economic Policy Uncertainty (EPU) Index. The EPU is weighted in the same way as bank home bias and is shown with four quarters lag. In the Figure, we see that the weighted bank home bias and the lagged weighted EPU index exhibit very similar patterns in terms of both general trends and short-run variations. In addition, we notice that the uncertainty index also remained high after the end of the Great Recession, the same as a prolonged period of high home bias. Further analysis shows that uncertainty has strong predictive power of bank home bias[15], which is consistent with the intuition as uncertainty itself is a forward-looking index. Therefore, the data confirms our assumption that uncertainty contributes to the high home bias period.

[15]The analysis can be found in the companion paper.

2.5 Conclusion

This paper analyzes the transmission of monetary policy through global bank lending. We provide empirical evidence on the variation of global banks' lending bias towards domestic loans for the past two decades, propose a tractable framework to shed light on the effects of monetary policy on banks' international lending, and extend the framework to dynamic general equilibrium environment to evaluate the dynamic impacts. Our empirical evidence shows that the *preferences* of global banks over lending location is increasingly biased towards the domestic country, and our structural analysis shows that such behavior is significantly driven by uncertainty variations. To account for this observation, our analytical framework shows that with the presence of uncertainty and costly endogenous risk management, the effects of monetary policy on lending allocation are ambiguous. Two opposite forces are present: On the one hand, expansionary monetary policy decreases the risk-free rate and thus increases domestic and cross-border bank lending. On the other hand, if the pass-through from the risk-free rate to the deposit rate is sufficiently low, expansionary monetary policy decreases bank profitability, lowers risk management activities, and hence discourages cross-border lending. We characterize the overall effects of monetary policy on bank home bias by a dichotomy of two regimes: in the *normal regime*, an expansionary monetary policy decreases home bias. On the contrary, in the *zero lower bound regime*, an expansionary monetary policy increases home bias as a bank profitability channel interacts with the risk management of foreign uncertainty frictions. Our model allows us to reconcile recent differences in the observed trends of equity and bank home bias. Finally, we extend our model to a dynamic setup and show that a prolonged period of low interest rates contributes to the high overshoot of home bias. Our analysis has relevant implications for the design of optimal monetary policy in currency unions.

We have started several potential directions to further this project. The first one is exploring the heterogeneity among banks. One main assumption in our paper is that each country has a representative banking sector, whereas, in reality, the distribution of banks in one country is hardly homogenous; rather, the size of the banks follows a distribution with larger national banks and smaller regional banks. As a result, the equity of the banks is also unevenly distributed across banks, and this heterogeneity might also constrain banks' ability to do cross-border lending. For instance, large banks, being too-big-to-fail, are considered a danger to the overall stability of the financial system. However, once we consider the cross-border lending ability, large banks might be better for cross-border investment because of the economy of scale of risk management. In this case, having more larger banks might be helpful for cross-border lending, thereby increasing the risk-sharing across borders and increasing overall stability. To this end, we develop a dynamic model with a heterogeneous banking sector in the following work, in which the banks have value functions and face uninsurable risks when investing in domestic and foreign countries. In addition, we assume the risk is endogenous to banks' wealth level. By doing so, we allow for a wealth effect on the bank's lending decision.

The second direction is to analyze the dynamic decision problem among countries. In the model, we assume that the two countries are symmetric and that banks make investment decisions simultaneously. Once we consider asymmetry across countries, it might as well be the case that the problem involves sequential moves. Capital-rich countries' banks, which are more capable of making decisions, choose the allocation of the investment across domestic and foreign countries. Based on these results, capital-poor countries' banks decide their allocation. In this case, if the capital-rich countries experience a negative shock to their banking sector and pull their money out of capital-poor countries, the economy in those poor countries will also experience negative shocks. Furthermore, if the capital-poor countries' banks have invested in rich countries, they might have no choice but to retreat as well to save their own banking sector, thereby exacerbating the negative shock in the rich countries. We believe that further research in these two directions will help us better assess the international impact of monetary policy changes.

2.6 Figures and Tables

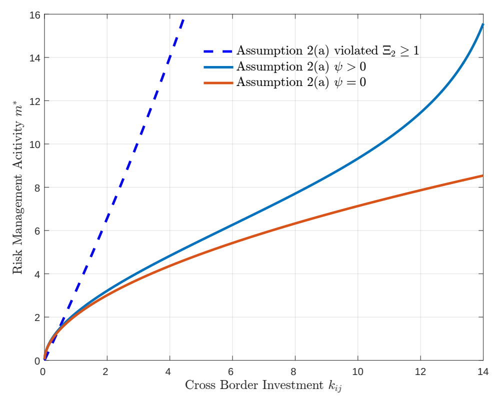

Figure 2.4: Optimal Uncertainty Management Activity m^*.

Notes: Figure 2.4 is constructed under the following parameter values: $\alpha = 1.00$, $\delta = 0.90$, $\eta = 0.75$, $\nu = 0.40$, $\varphi^{uc} = 1.00$, $\varphi^c = \frac{1+2\eta}{2(1-\nu)} + 0.25$, $\chi^{uc} = 1.10$, $\chi^c = \frac{2\varphi^c(1-\nu)}{1+2\eta}$, $\lambda^{uc} = 1.20$, $\lambda^c = 1 + \frac{\chi^c}{2\varphi^c}$, $\sigma_\epsilon = 2.00$, $\psi \in \{0.00, 0.50\}$, $\theta = 0.75$, $\omega = 0.05$, $\mu_i = \mu_j = 0.25$, $c_i = 0.20$, $r^f = 0.10$, $k_{ii} = 1.00$, $w_i = 2$.

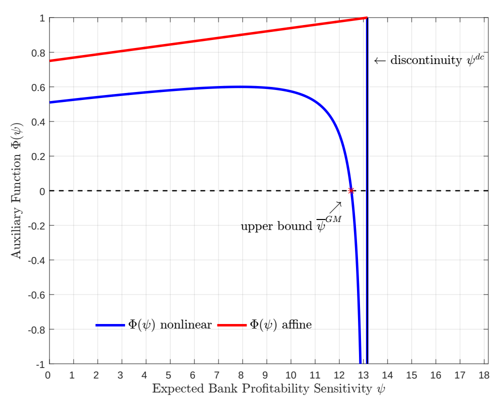

Figure 2.5: Auxiliary Function $\Phi(\psi)$ and Parameter Space of Equity Managing Impact ψ.

Notes: The above figure is constructed under the following parameter values: $\theta = 0.75$, $\zeta_i = 1.20$, $\mu_i = \mu_j = 0.25$, $\sigma_i = \sigma_j = 1.00$, $\sigma_m = 0.75$, $r^m = 0.10$. The affine functional specification uses consequently $\rho = 0.50$, whereas the nonlinear specification imposes $\rho = 0.70$.

Table 2.1: Parameters.

Parameter	Description	Value
α	CARA risk-aversion	4.750
β	discount factor	0.990
μ_i & μ_j	mean of return on domestic and foreign project	1.025
σ_i & σ_j	standard deviation of domestic and foreign project return	0.550
ρ	correlation between domestic and foreign project	0.200
σ_ϵ	standard deviation of uncertainty	1.2 $\times \sigma_i$
ω	pass-through elasticity from risk-free rate to deposit rate	0.950
δ	deposit to asset ratio	0.850
ζ	Overall management efficiency	0.950
ψ	Management cost reduction w.r.t wealth	1.000
κ_d	Pledgeability of domestic loan	0
κ_f	Pledgeability of foreign loan	0
τ	regulation cost on risky projects	0.000
θ	bargain parameter	1.000
$\bar{d}$	deposit supply function parameter	4.000
Θd	deposit supply function parameter	6.000

Table 2.2: Conventional Parameters

Parameter	Description	Value
σ	Elasticity of consumption	1
χ	relative utility of labor	1.75
φ	elasticity of labor	1
α_k	capital share	0.33
δ_k	capital depreciation rate	0.025
ϕ	Rotemberg cost parameter	60
ϵ_p	CES substitution elasticity	5
ρ_i	policy rate persistence	0.8
ϕ_π	Taylor rule parameter for inflation	1.5

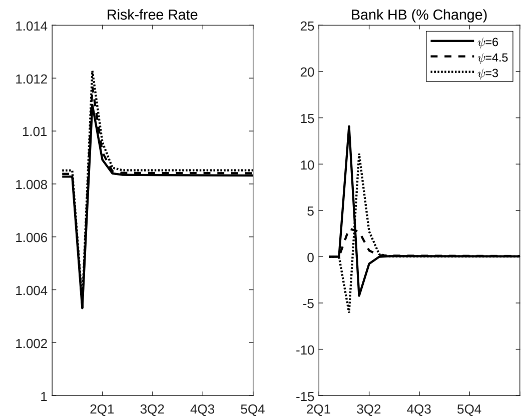

Figure 2.6: Responses of Bank Home Bias to one-period Rate Cut.

Notes: The dashed and dotted shows the responses with different degree of ψ.

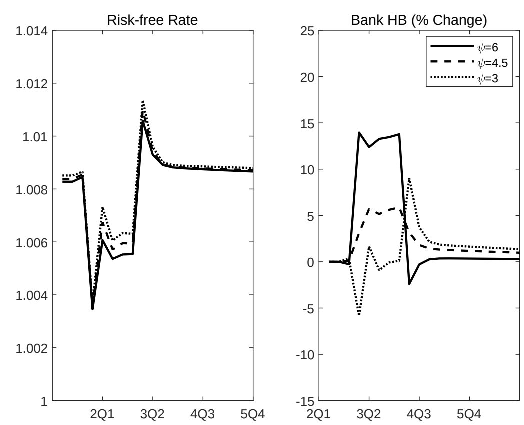

Figure 2.7: Responses of Bank Home Bias to Persistent Low Rates.

Notes: The dashed and dotted shows the responses with difference degrees of the wealth pledgeability paramter ψ.

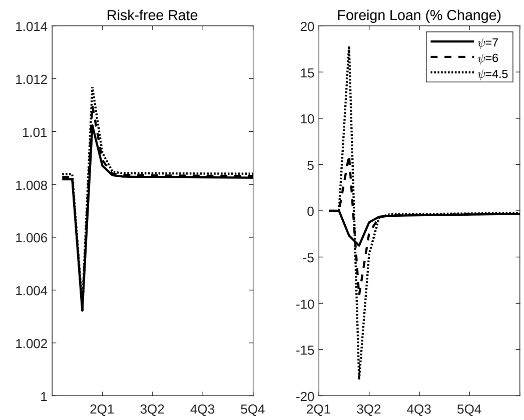

Figure 2.8: Responses of Foreign Lending Quantity.

Notes: The dashed and dotted shows the responses with different degree of ψ.

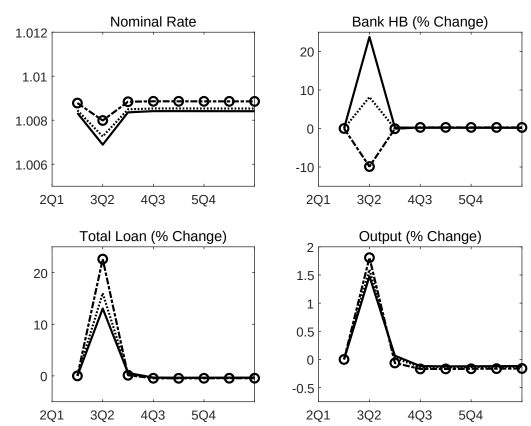

Figure 2.9: Responses of to Nominal Rate Cut.

Notes: The solid line, dash line, and dash line with circles are respectively the impulse responses of the model with ψ equal to 6, 4 and 2.

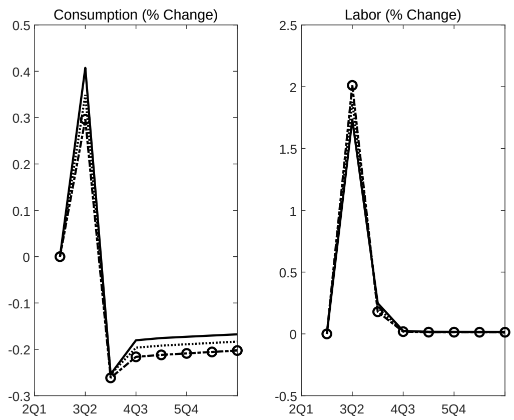

Figure 2.10: Responses of to Nominal Rate Cut.

Notes: The solid line, dash line, and dash line with circles are respectively the impulse responses of the model with ψ equal to 6, 4 and 2.

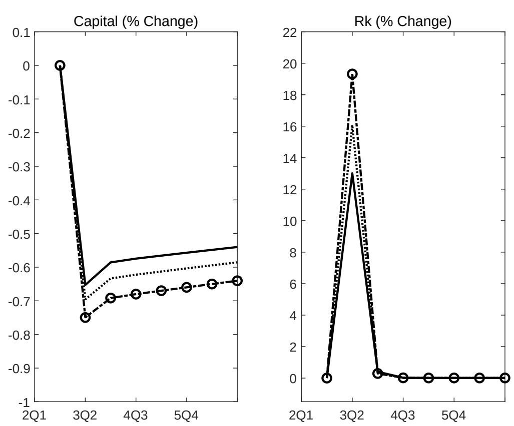

Figure 2.11: Responses of to Nominal Rate Cut.

Notes: The solid line, dash line, and dash line with circles are respectively the impulse responses of the model with ψ equal to 6, 4 and 2.

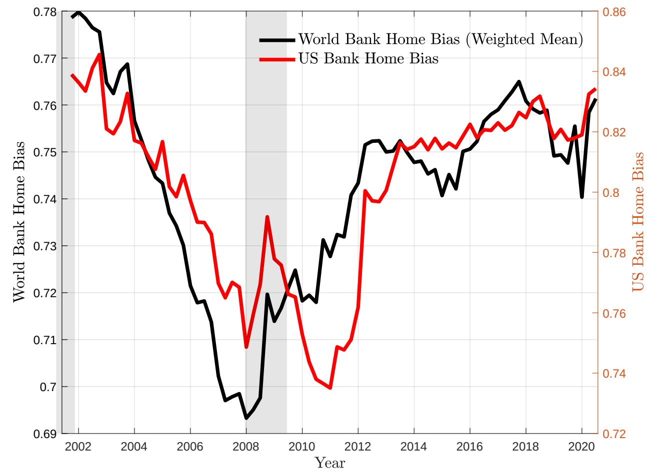

Figure 2.12: Bank Home Bias Fluctuations.

Notes: The dark line displays the average level of bank home bias of the countries in our sample at quarterly frequency, from 2001 Q4 to 2020 Q2. Weights are computed based on the size of their banking sectors' total assets. The red line displays the home bias of US banks.

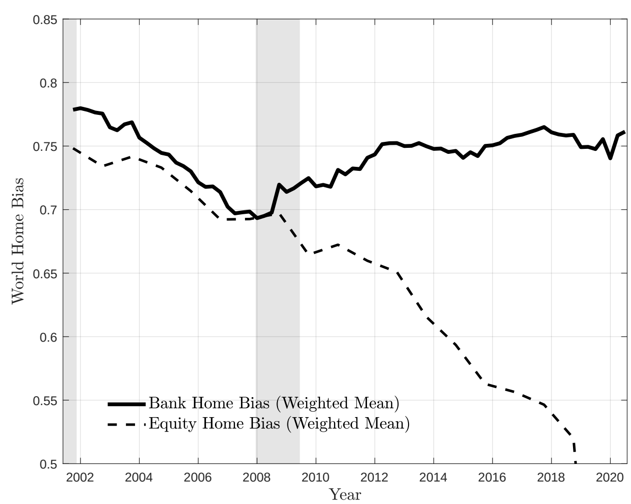

Figure 2.13: World Bank home bias vs. World equity home bias.

Note: The solid line shows the average level of bank home bias weighted by total bank asset, as in Figure 2.12. The dash line shows the average equity home bias weighted by GDP computed in large sample. The blue shaded area is the [25, 50] quantile of the equity home bias panel dataset. For the equity home bias values of each country, see Table 2.

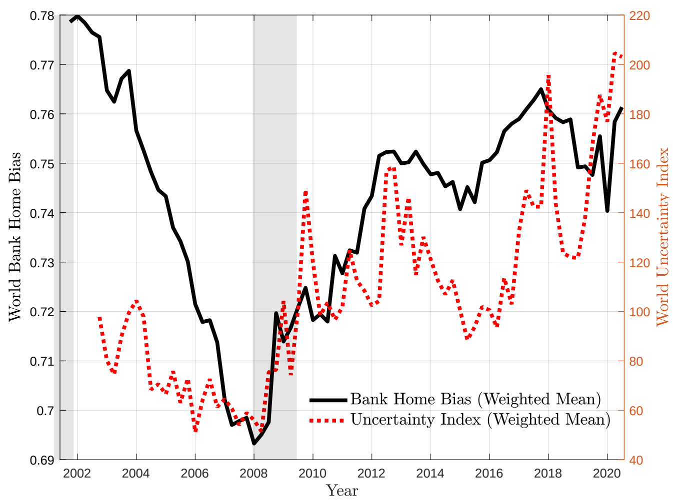

Figure 2.14: Weighted Mean of World Bank Home Bias and Uncertainty.

Note: The solid line shows the average level of bank home bias weighted by total bank asset, as in Figure 2.12. The red dash line shows the average Economic Policy Uncertainty index weighted by total bank assets, lagged by 4 quarters.

2.7 Appendix

2.7.1 Static Model Derivations and Proofs

Auxiliary Assumptions

Assumption 4.

Assumption 4 (Tractability). *The following assumptions hold.*

(a) Risk reduction and management cost elasticities $(\varphi, \eta, \lambda, \chi, \nu)$ relate to each other according to

$$2\frac{(1+\eta)\chi+\varphi\nu}{\chi+2\varphi}=1 \quad \textit{and} \quad \lambda=\frac{\chi+2\varphi}{2\varphi} \ .$$

(b) The variances of the fundamental technology shocks are given by

$$\sigma^2_{z_i}=\frac{1}{\theta^2(1-\xi)^2}\sigma^2_i \ , \quad \textit{and} \quad \sigma^2_{z_j}=\frac{1}{\theta^2(1-\xi)^2}\sigma^2_j$$

Auxiliary Lemmas

Lemma 5.

Lemma 5 (Distribution of Terminal Equity). *As stated previously, our static bank environment relies on an underlying CARA-Normal structure. We thus first characterize the distribution of terminal period equity in Lemma 5.*

Terminal equity e'_i follows a Normal distribution, i.e. $e'_i \sim \mathcal{N}(\mu_{e'_i}, \sigma^2_{e'_i})$. Under Assumption 4 (b), its mean and variance are given by

$$\begin{aligned}
\mu_{e'_i} &= (1+r^m)e_i + (1-\omega)r^m d_i + \theta(\mu_i - r^m)k_{ii} + \theta(\mu_j - r^m)k_{ij} - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i{}') \ , \\
\sigma^2_{e'} &= \sigma^2_i k^2_{ii} + \left(\sigma^2_j + \sigma^2_\epsilon(1-\mathcal{P}(m,k_{ij}))^2\right)k^2_{ij} + 2\rho\sigma_i\sigma_j k_{ii}k_{ij} \ ,
\end{aligned}$$

where (μ_i, μ_j) are defined according to

$$\mu_i \equiv (1-\xi)\mu_{z_i} - 1 \ , \quad \textit{and} \quad \mu_j \equiv (1-\xi)\mu_{z_j} - 1 \ .$$

The expected bank profitability before uncertainty management activities is given by

$$\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right] = (1-\omega\delta)\, r^m w_i + \theta(\mu_i - r^m)k_{ii} + \theta(\mu_j - r^m)k_{ij} \ . \quad (2.7.1)$$

The mean of terminal equity increases in the risk premium of investment projects, i.e. it increases in θ and decreases in ζ. The effects of a tightening of monetary policy are *ex ante* ambiguous as multiple channels simultaneously impact expected profitability. On the one hand, an increase in r^f decreases the risk premium and hence suppresses both domestic as well as cross-border lending and thus expected profitability. On the other hand, an increase in r^f raises the returns on risk-free asset holdings, i.e. on the part $w_i - k_{ii} - k_{ij}$ of initial wealth which is hold as central bank reserves. Additionally, monetary policy also acts on the liability side of the balance sheet because of interest rate pass-through from the monetary policy rate to the deposit rate. For the effect of contractionary monetary policy on the equity mean to be positive, it is required that either there is little pass-through from the monetary policy rate to the deposit rate, i.e. ω is low, or the bank is not highly leveraged, δ is low, such that $(1 - \omega\delta) > 0$ is satisfied. In this case, we say that there is a risk-free rate arbitrage, meaning that under this circumstances, banks earns profit simply through collecting deposit and put them into safe asset. The return on the safe asset is sufficient to cover all deposit payment.

Lemma 6.

Lemma 6 (Upper Limit Bank Profitability Sensitivity)**.** *$\Phi(\psi)$ is discontinuous at the point*

$$\psi^{dc} = \frac{\sigma_j^2}{\zeta_i\theta(\mu_j - r^f)\sigma_\epsilon^2} \,.$$

(a) If $2\rho\frac{\mu_j - r^m}{\sigma_j} = \frac{\mu_i - r^m}{\sigma_i}$ holds, $\Phi(\psi)$ is an affine function in ψ which lies in $\mathbb{R}_+$ if $2\frac{\sigma_i}{\sigma_j} \geq \frac{\mu_i - r^m}{\mu_j - r^m}$.

(b) If on the contrary $2\rho\frac{\mu_j - r^m}{\sigma_j} \neq \frac{\mu_i - r^m}{\sigma_i}$ holds, $\Phi(\psi)$ has a positive and a negative root, in which interval the function is positive. Thus, there exists a parameter set $\Psi^{GM} \equiv \left[0, \overline{\psi}^{GM}\right)$ on which Φ is strictly positive, and decreasing in ρ at $\psi = 0$. The upper bound $\overline{\psi}^{GM} < \psi^{dc}$ is given by

$$\overline{\psi}^{GM} = \Gamma\left([\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)] + \left([\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)]^2 + (\mu_i - r^m)^2(1-\rho^2)\sigma_j^2 \right)^{\frac{1}{2}} \right) ,$$

with $\Gamma \equiv \frac{2\sigma_i}{\zeta_i\theta\sigma_\epsilon^2(\mu_i - r^m)^2}$ holds.

Lemma 7.

Lemma 7 (Optimal Monitoring Effort)**.** *The comparative statics are as follows*

$$\frac{dm^*}{d\alpha} = \Omega_\alpha > 0 \,, \quad \frac{dm^*}{d\sigma_{\epsilon_t}^2} = \Omega_{\sigma_\epsilon^2} > 0 \,, \quad \frac{dm^*}{dk_{ij}} = \Omega_k \gtrless 0 \,,$$

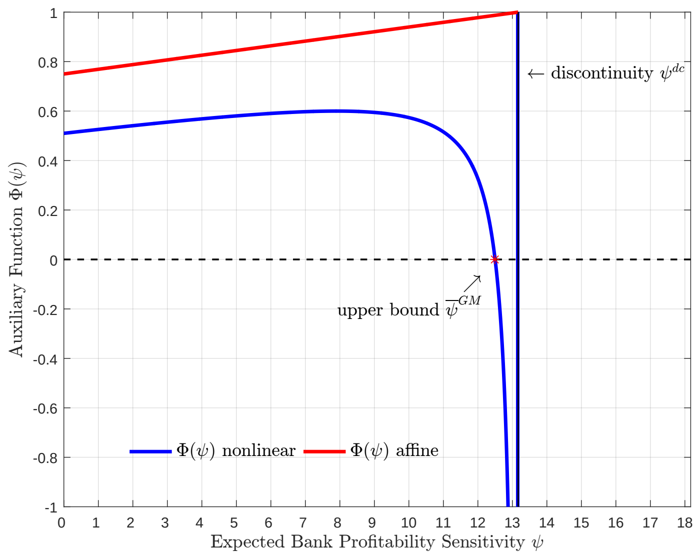

Figure 2.15: Auxiliary Function $\Phi(\psi)$ and Parameter Space of Equity Managing Impact ψ.

Notes: The above figure is constructed under the following parameter values: $\theta = 0.75$, $\zeta_i = 1.20$, $\mu_i = \mu_j = 0.25$, $\sigma_i = \sigma_j = 1.00$, $\sigma_\epsilon = 0.75$, $r^m = 0.10$. The affine functional specification uses consequently $\rho = 0.50$, whereas the nonlinear specification imposes $\rho = 0.70$.

where the auxiliary parameters are given by

$$\Omega_\alpha = \frac{\sigma_\epsilon^2(1-\mathcal{P})k_{ij}^2\mathcal{P}_m}{\mathcal{C}_{mm} + \alpha\sigma_\epsilon^2 k_{ij}^2\left(\mathcal{P}_m^2 - (1-\mathcal{P})\mathcal{P}_{mm}\right)} \,,$$

$$\Omega_{\sigma_\epsilon^2} = \frac{\alpha(1-\mathcal{P})k_{ij}^2\mathcal{P}_m}{\mathcal{C}_{mm} + \alpha\sigma_\epsilon^2 k_{ij}^2\left(\mathcal{P}_m^2 - (1-\mathcal{P})\mathcal{P}_{mm}\right)} \,,$$

$$\Omega_k = \frac{\alpha\sigma_\epsilon^2\left[-\mathcal{P}_m\mathcal{P}_k k_{ij}^2 + 2(1-\mathcal{P})\mathcal{P}_m k_{ij} + (1-\mathcal{P})\mathcal{P}_{mk}k_{ij}^2\right] - \mathcal{C}_{mk} - \mathcal{C}_{m,\Delta\tilde{e}_i'}\frac{\partial\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}{\partial k_{ij}}}{\mathcal{C}_{mm} + \alpha\sigma_\epsilon^2 k_{ij}^2\left(\mathcal{P}_m^2 - (1-\mathcal{P})\mathcal{P}_{mm}\right)} \,.$$

Proof: Lemma

Proof Lemma 1.

Proof. As stated in the main body of the text, expected bank profitability before risk management costs is given by

$$\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right] = \left[1-\omega\delta\right] r^f w_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} \,.$$

Taking the derivative with respect to r^f yields

$$\frac{\partial \mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}{\partial r^f} = (1-\omega\delta)w_i - \theta(k_{ii}+k_{ij}) + \theta(\mu_i - r^f)\frac{\partial k_{ii}}{\partial r^f} + \theta(\mu_j - r^f)\frac{\partial k_{ij}}{\partial r^f} .$$

Using the initial period budget constraint and the assumption of equality of risk premia across investment opportunities, i.e. $\mu_i = \mu_j = \mu$, we obtain

$$\begin{aligned}\frac{\partial \mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}{\partial r^f} &= (1-\omega\delta-\theta)w_i + \theta b_i + \theta(\mu - r^f)\left(\frac{\partial k_{ii}}{\partial r^f} + \frac{\partial k_{ij}}{\partial r^f}\right) \\ &= (1-\omega\delta-\theta)w_i + \theta b_i + \frac{\theta(\mu - r^f)}{r^f}\left(\varepsilon_{k_{ii},r^f}k_{ii} + \varepsilon_{k_{ij}}k_{ij}\right) ,\end{aligned}$$

where the second equality by using the elasticity identities $\varepsilon_{k_{ii},r^f} \equiv \frac{\partial k_{ii}}{\partial r^f}\frac{r^f}{k_{ii}}$ and $\varepsilon_{k_{ij},r^f} \equiv \frac{\partial k_{ij}}{\partial r^f}\frac{r^f}{k_{ij}}$. The above equation is weakly positive if

$$\frac{b_i}{w_i} \geq \frac{\theta+\omega\delta-1}{\theta} - \frac{\mu - r^f}{r^f}\left(\varepsilon_{k_{ii},r^f}\kappa_{ii} + \varepsilon_{k_{ij}}\kappa_{ij}\right) ,$$

where $\kappa_{ii} \equiv \frac{k_{ii}}{w_i}$ and $\kappa_{ij} \equiv \frac{k_{ij}}{w_i}$. This completes the proof of Lemma 1. □

Proof Lemma 2.

Proof. To begin with, we impose for a positive and finite cross border investment level k_{ij} that the risk reduction function $\mathcal{P}(m, k_{ij})$ is subject to the following restrictions

(i) $\mathcal{P}(m, k_{ij}) \in (-\infty, 1]$, where $\lim_{m\to 0}\mathcal{P}(m, k_{ij}) = -\infty$ and $\lim_{m\to\infty}\mathcal{P}(m, k_{ij}) = 1$.

(ii) $\frac{\partial \mathcal{P}(m,k_{ij})}{\partial m} > 0$, $\frac{\partial^2 \mathcal{P}(m,k_{ij})}{\partial m^2} < 0$, $\frac{\partial \mathcal{P}(m,k_{ij})}{\partial k_{ij}} < 0$ and $\frac{\partial^2 \mathcal{P}(m,k_{ij})}{\partial m \partial k_{ij}} > 0$.

Restriction (i) provides conditions on the support of $\mathcal{P}(m, k_{ij})$. If bankers invest zero effort in risk managing activities, uncertainty σ_ϵ^2 is scaled up. On the contrary, if bankers invest infinite effort into risk managing activities, uncertainty can be reduced to zero. Moreover, we assume that the risk reduction function is strictly increasing and strictly concave in the effort level m. We also assume that the risk reduction of a given effort m decreases in the risky cross border investment level k_{ij} and that risky cross border investment and effort behave in a *complementary* manner.

Contrary, the cost function associated with risk management, $\mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i')$, has the subsequent properties

(iii) $\mathcal{C}(0, k_{ij}, \Delta\tilde{e}_i') = \mathcal{C}(m, 0, \Delta\tilde{e}_i') = \mathcal{C}_m(0, k_{ij}, \Delta\tilde{e}_i') = 0$.

(iv) $\frac{\partial \mathcal{C}(m,k_{ij},\Delta\tilde{e}_i')}{\partial m} > 0$, $\frac{\partial^2 \mathcal{C}(m,k_{ij},\Delta\tilde{e}_i')}{\partial m^2} > 0$, $\frac{\partial \mathcal{C}(m,k_{ij},\Delta\tilde{e}_i')}{\partial k_{ij}} \gtrless 0$, and $\frac{\partial^2 \mathcal{C}(m,k_{ij},\Delta\tilde{e}_i')}{\partial m \partial k_{ij}} \gtrless 0$.

Property (iii) states that effort costs only arise if the effort level and cross border investment are positive. Additionally, the cost function is strictly convex in its first argument, increasing or decreasing in its second argument, and complementary or substitutable in both of its arguments.

Due to the CARA-Normal structure, one can state the risk management objective of (P1) as

$$\max_{\{m\}} -\frac{1}{2}\alpha\sigma_\epsilon^2 \Big(1 - \mathcal{P}(m, k_{ij})\Big)^2 k_{ij}^2 - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}_i') \,, \tag{P2'}$$

Taking the first order condition, we get

$$\mathcal{C}_m(m, k_{ij}, \Delta\tilde{e}_i') = \alpha\sigma_\epsilon^2 \Big(1 - \mathcal{P}(m, k_{ij})\Big) k_{ij}^2 \mathcal{P}_m(m, k_{ij}) \,. \tag{2.7.2}$$

To ensure that the solution characterizes indeed a maximum, we verify by means of the second order condition

$$-\mathcal{C}_{mm}(m, k_{ij}, \Delta\tilde{e}_i') + \alpha\sigma_\epsilon^2 \Big(1 - \mathcal{P}(m, k_{ij})\Big) k_{ij}^2 \mathcal{P}_{mm}(m, k_{ij}) - \alpha\sigma_\epsilon^2 k_{ij}^2 \mathcal{P}_m^2(m, k_{ij}) < 0 \,.$$

To rule out the boundary case $m = 0$, we need to ensure that the following inequality holds

$$\alpha\sigma_\epsilon^2 \Big(1 - \mathcal{P}(0, k_{ij})\Big) k_{ij}^2 \mathcal{P}_m(0, k_{ij}) > \mathcal{C}_m(0, k_{ij}, \Delta\tilde{e}_i') \,,$$

which is trivially satisfied if $\mathcal{P}_m(0, k_{ij}) > 0$ given our initial assumptions on the variance scaling function as well as the cost function. Differentiating equation (2.7.2) and applying the implicit function theorem, we obtain Lemma 7 for the comparative statics for optimal monitoring effort.

The optimal managing activity m^* increases both in the coefficient of absolute risk aversion α and in the uncertainty variance σ_ϵ^2. Contrary, the sign of the comparative statics with respect to the first stage investment k_{ij} is arbitrary. This is due to the assumption, that managing costs may be increasing in initial investments.

Next, we solve the risk management problem parametrically. To do so, we first restate the parametric forms specified in the main text:

$$\mathcal{P}(m,k_{ij}) = 1 - m^{-\varphi}k_{ij}^{\eta}\,, \quad \text{and} \quad \mathcal{C}(m,k_{ij},\Delta\tilde{e}'_i) = \frac{1}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\lambda} m^{\chi}k_{ij}^{\nu}\,,$$

where $\{\varphi,\eta\}$ denote the elasticities of the *effective* variance scaling factor $1-\mathcal{P}(m,k_{ij})$ with respect to managing activity m, respectively first stage investment k_{ij}. Similarly, $\{\chi,\nu\}$ denote the elasticities of the cost function with respect to m, respectively k_{ij}. Under the previous parametric forms, we can rewrite the first order condition (2.7.2) as

$$\begin{aligned} & c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\lambda} m^{\chi-1}k_{ij}^{\nu} = \alpha\varphi\sigma_\epsilon^2 m^{-2\varphi-1}k_{ij}^{2(1+\eta)}\,, \\ \Leftrightarrow & m^* = \left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{1}{\chi+2\varphi}} c_i^{-\frac{\lambda}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}}\,. \end{aligned} \tag{2.7.3}$$

Resubstitution into the objective function (P2′) results in the following certainty equivalent

$$\mathbb{CE}\left(m^*,k_{ij}\right) = -\frac{1}{2}\alpha\sigma_\epsilon^2(m^*)^{-2\varphi}k_{ij}^{2(1+\eta)} - \frac{1}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\lambda}(m^*)^{\chi}k_{ij}^{\nu}\,.$$

Using the explicit expression from equation (2.7.3), we can simplify to

$$\begin{aligned} \mathbb{CE}\left(m^*,k_{ij}\right) = & -\frac{1}{2}\alpha\sigma_\epsilon^2\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{-2\varphi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{-2\varphi[(2(1+\eta)-\nu]+2(\chi+2\varphi)(1+\eta)}{\chi+2\varphi}} \\ & -\frac{1}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\lambda}\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}} c_i^{-\frac{\lambda\chi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{-\frac{\lambda\chi}{\chi+2\varphi}} k_{ij}^{\frac{\chi[2(1+\eta)-\nu]+\nu(\chi+2\varphi)}{\chi+2\varphi}} \\ = & -\frac{1}{2}\left(\alpha\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}}\varphi^{\frac{-2\varphi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}} \\ & -\frac{1}{\chi}\left(\alpha\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}}\varphi^{\frac{\chi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}} \\ = & -\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}}\left(\frac{1}{2}\varphi^{-1}+\frac{1}{\chi}\right) \\ = & -\frac{\chi+2\varphi}{2\varphi\chi}\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}'_i|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}}\,. \end{aligned}$$

Under Assumption 4, the previous expression maps into the imposed form of manageable risk from Lemma 1 if

$$\zeta_i \equiv \frac{\chi+2\varphi}{\chi}\left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\,, \quad \text{and} \quad \sigma_\epsilon^2 \equiv \left(\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}}\,.$$

As a result, we obtain

$$\mathbb{CE}\left(m^*, k_{ij}\right) = -\frac{1}{2}\alpha\zeta_i\left(1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)\sigma_\epsilon^2 k_{ij} \tag{2.7.4}$$

and the manageable risk result of Lemma 1 follows. Notice that the inverse managing ability ζ_i is a functional of risk aversion α, the marginal cost shifter c_i, and the elasticities $\{\chi, \varphi, \lambda\}$ of the cost function and the effective variance scaling factor w.r.t. managing activity. Based on Assumption 4 we impose the following equality

$$\frac{2\left[(1+\eta)\chi + \nu\varphi\right]}{\chi + 2\varphi} = 1 \Leftrightarrow \chi = \frac{2\varphi(1-\nu)}{1+2\eta}\,,$$
$$\frac{2\lambda\varphi}{\chi + 2\varphi} = 1 \Leftrightarrow \chi = 2\varphi(\lambda - 1)\,.$$

On behalf of the two previous identities, we obtain in a straightforward manner

$$\chi = \frac{\varphi(\lambda - \nu)}{1+\eta}\,.$$

In order to be consistent with the general assumptions on the variance scaling function as well as the cost function, we need to impose the following parameter space

$$\varphi > \frac{1+2\eta}{2(1-\nu)} = \frac{1}{2(\lambda-1)} = \frac{1+\eta}{\lambda-\nu}\,, \quad 0 < \nu < 1\,, \eta > 0\,, \lambda = 1 + \frac{\chi}{2\varphi} > 1$$

where the inequality is due to the strict convexity of the costs function in managing activity, i.e. $\chi > 1$. Substituting in for χ, we can rewrite managing ability as

$$\zeta_i(\varphi, \eta, \nu, \alpha, c_i) = \left(\frac{2(1+\eta) - \nu}{1-\nu}\right)(\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i\,,$$

where the previous equality follows from

$$\frac{\chi + 2\varphi}{\chi} = \frac{\frac{2\varphi(1-\nu)}{1+2\eta} + 2\varphi}{\frac{2\varphi(1-\nu)}{1+2\eta}} = \frac{2\varphi(1-\nu) + 2\varphi(1+2\eta)}{2\varphi(1-\nu)} = \frac{2(1+\eta) - \nu}{1-\nu}\,,$$
$$-\frac{2\varphi}{\chi + 2\varphi} = -\frac{2\varphi}{\frac{2\varphi(1-\nu)}{1+2\eta} + 2\varphi} = -\frac{2\varphi(1+2\eta)}{2\varphi(1-\nu) + 2\varphi)(1+2\eta)} = -\frac{1+2\eta}{2(1+\eta) - \nu}\,.$$

□

Proof Lemma 3.

The proof of Lemma 3 proceeds in two steps. In the first step, we derive a sufficient upper bound on the correlation ρ such that cross border investment is weakly positive. In a second step, we derive upper bounds on risk management cost reduction ψ such that statements (a) and (b) follow.

Proof. Part I: Sufficient Condition for Positivity of Cross Border Investment
Under Assumption 3 on the symmetry of model parameters across countries, cross border investment is given by

$$k_{ij} = k_{ji} = \Phi^{-1}\left(\frac{\theta(\mu - r^m)}{\alpha\left(\sigma^2 - \zeta\psi\theta(\mu - r^m)\sigma_\epsilon^2\right)} - \Theta\frac{\theta(\mu - r^m)}{\alpha\sigma^2} - \frac{1}{2}\zeta\sigma_\epsilon^2\frac{1-\psi(1-\omega\delta)r^f w}{\sigma^2 - \zeta\psi\theta(\mu - r^m)\sigma_\epsilon^2}\right),$$

where the auxiliary parameters are now given by

$$\Phi = 1 - \frac{1}{\sigma^2}\frac{(\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2)^2}{\sigma^2 - \zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2},$$
$$\Theta = \frac{\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2}{\sigma^2 - \zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2}.$$

For $\psi < \overline{\psi}^{GM,s} < \psi^{dc,s}$, we know that $\Phi > 0$. As a result, cross border investments are weakly positive if the following inequality holds:

$$\frac{\theta(\mu - r^m)}{\alpha} - \frac{\theta(\mu - r^m)}{\alpha\sigma^2}\left(\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2\right) - \frac{1}{2}\zeta\sigma_\epsilon^2\left[1 - \psi(1-\omega\delta)r^f w\right] \geq 0\,.$$

The left hand side of the previous equation is increasing in ψ, as $\mu - r^f \geq 0$ and $\omega\delta \leq 1$. As a result, a sufficient condition for cross border investment to be positive is given by

$$\frac{\theta(\mu - r^m)}{\alpha}(1-\rho) - \frac{1}{2}\zeta\sigma_\epsilon^2 \geq 0 \Leftrightarrow \rho \leq \overline{\rho} \equiv 1 - \frac{1}{2}\frac{\alpha\zeta\sigma_\epsilon^2}{\theta(\mu - r^f)}\,. \tag{2.7.5}$$

Part II: Upper Bound Risk Management Cost Sensitivity
To begin with, statement (b) is satisfied if the following upper bound applies

$$\psi^{(b),s} \leq \frac{1}{(1-\omega\delta)r^f w}\,. \tag{2.7.6}$$

This upper limit ensures that cross border information frictions are always detrimental for bankers such that they cannot exploit the friction in order to better off. If $\psi = 0$ statement (b) is obviously satisfied. Contrary, if $\psi > 0$ it requires that $\omega\delta$ is either above a certain level, or ψ

below the threshold (2.7.6).

To verify statement (a), for $\psi < \overline{\psi}^{GM,s} < \psi^{dc,s}$ and thus $\Phi > 0$, domestic investment of bankers exceeds cross border investment, i.e. $k_{ii} = k_{jj} \geq k_{ij} = k_{ji}$ if the following inequality holds

$$\frac{\theta(\mu - r^m)}{\alpha\sigma^2} + \frac{1}{2}\frac{\zeta\sigma_\epsilon^2}{\sigma^2}\Theta\left[1 - \psi(1-\omega\delta)r^m w\right] \geq \frac{\theta(\mu - r^m)}{\alpha\left(\sigma^2 - \zeta\psi\theta(\mu - r^m)\sigma_\epsilon^2\right)} - \frac{1}{2}\zeta\sigma_\epsilon^2\frac{1-\psi(1-\omega\delta)r^f w}{\sigma^2 - \zeta\psi\theta(\mu - r^m)\sigma_\epsilon^2}\,,$$

which can be easily rewritten as

$$-\frac{\theta(\mu - r^m)}{\alpha\sigma^2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2 + \frac{1}{2}\zeta\sigma_\epsilon^2\left[1 - \psi(1-\omega\delta)r^m w\right]\left(\frac{\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2}{\sigma^2} + 1\right) \geq 0\,,$$

Canceling terms results in

$$-\frac{\theta^2(\mu - r^m)^2}{\alpha}\psi + \frac{1}{2}\left[1 - \psi(1-\omega\delta)r^m w\right]\left((1+\rho)\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu - r^f)\sigma_\epsilon^2\right) \geq 0\,.$$

The previous inequality obviously holds if $\psi = 0$ or $\mu = r^f$ as $\rho \in (-1, 1)$ and $\sigma^2 > 0$. The left hand side is a quadratic polynomial in ψ, i.e. $\mathcal{A}\psi^2 + \mathcal{B}\psi + \mathcal{C}$ with corresponding coefficients

$$\begin{aligned}
\mathcal{A} &= \frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2(1-\omega\delta)r^m w\,,\\
\mathcal{B} &= -\frac{\theta^2(\mu - r^m)^2}{\alpha} - \frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2 - \frac{1}{2}(1-\omega\delta)r^m w(1+\rho)\sigma^2\,,\\
\mathcal{C} &= \frac{1}{2}(1+\rho)\sigma^2\,.
\end{aligned}$$

As a result, the left hand side is a strictly convex parabola in ψ. As it takes the strictly positive value $\frac{1}{2}(1+\rho)\sigma^2$ at $\psi = 0$, its two possible roots necessarily lie in $\mathbb{R}_+$. They are given by

$$\psi_{1,2}^{(a)} = \frac{\mathcal{B} \pm \sqrt{\mathcal{B}^2 - 4\mathcal{A}\mathcal{C}}}{2\mathcal{A}}\,.$$

The corresponding discriminant $\mathcal{D} = \mathcal{B}^2 - 4\mathcal{A}\mathcal{C}$ is given in turn by

$$\begin{aligned}
\mathcal{D} =& \frac{\theta^4(\mu - r^m)^4}{\alpha^2} + \frac{1}{16}\zeta^2\theta^2(\mu - r^f)^2(\sigma_\epsilon^2)^2 + \frac{1}{4}(1-\omega\delta)^2(r^m)^2 w^2(1+\rho)^2(\sigma^2)^2\\
&+ \frac{1}{2}\zeta\sigma_\epsilon^2\frac{\theta^3(\mu - r^m)^3}{\alpha} + \frac{\theta^2(\mu - r^m)^2}{\alpha}(1-\omega\delta)r^m w(1+\rho)\sigma^2\\
&+ \frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2(1-\omega\delta)r^m w(1+\rho)\sigma^2 - \frac{1}{2}\zeta\theta(\mu - r^f)\sigma_\epsilon^2(1-\omega\delta)r^m w(1+\rho)\sigma^2
\end{aligned}$$

The right hand side of the previous expression can be simplified to

$$\frac{\theta^4(\mu - r^m)^4}{\alpha^2} + \frac{1}{16}\zeta^2\theta^2(\mu - r^f)^2(\sigma_\epsilon^2)^2 + \frac{1}{4}(1-\omega\delta)^2(r^m)^2 w^2(1+\rho)^2(\sigma^2)^2$$
$$+ \frac{1}{2}\zeta\sigma_\epsilon^2\frac{\theta^3(\mu - r^m)^3}{\alpha} + \frac{\theta^2(\mu - r^m)^2}{\alpha}(1-\omega\delta)r^m w(1+\rho)\sigma^2 - \frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2(1-\omega\delta)r^m w(1+\rho)\sigma^2\,,$$

which finally results in

$$\mathcal{D} = \frac{\theta^4(\mu - r^m)^4}{\alpha^2} + \frac{1}{2}\zeta\sigma_\epsilon^2\frac{\theta^3(\mu - r^m)^3}{\alpha} + \frac{\theta^2(\mu - r^m)^2}{\alpha}(1-\omega\delta)r^m w(1+\rho)\sigma^2$$
$$+ \left(\frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2 - \frac{1}{2}(1-\omega\delta)r^f w(1+\rho)\sigma^2\right)^2 \geq 0\,,$$

where the positivity follows from the quadratic expression. Let us denote the smaller root by $\psi_1^{(a),s}$ and the larger one respectively by $\psi_2^{(a),s}$. Due to the positivity of the discriminant as well as the positivity of $\mathcal{A}$ it is evident that $\psi_2^{(a),s} \geq \frac{\mathcal{B}}{2\mathcal{A}}$. The latter term is pinned down by

$$\begin{aligned}
\frac{\mathcal{B}}{2\mathcal{A}} &= \frac{\frac{\theta^2(\mu - r^m)^2}{\alpha} + \frac{1}{4}\zeta\theta(\mu - r^f)\sigma_\epsilon^2 + \frac{1}{2}(1-\omega\delta)r^m w(1+\rho)\sigma^2}{\frac{1}{2}\zeta\theta(\mu - r^f)\sigma_\epsilon^2(1-\omega\delta)r^m w} \\
&= \frac{1}{2}\frac{1}{(1-\omega\delta)r^m w} + 2\frac{\theta(\mu - r^f)}{\alpha\zeta\sigma_\epsilon^2(1-\omega\delta)r^m w} + \frac{(1+\rho)\sigma^2}{\zeta\theta(\mu - r^f)\sigma_\epsilon^2} \\
&= \frac{1}{(1-\omega\delta)r^m w}\left[\frac{1}{2} + 2\frac{\theta(\mu - r^f)}{\alpha\zeta\sigma_\epsilon^2}\right] + \frac{(1+\rho)\sigma^2}{\zeta\theta(\mu - r^f)\sigma_\epsilon^2} \\
&\geq \frac{1}{(1-\omega\delta)r^m w}\left[\frac{1}{2} + \frac{1}{1-\rho}\right] + \frac{(1+\rho)\sigma^2}{\zeta\theta(\mu - r^f)\sigma_\epsilon^2} \geq \frac{1}{(1-\omega\delta)r^m w}\,,
\end{aligned}$$

where the first inequality arises due to the correlation upper bound $\bar{\rho}$, which implies that $2\theta(\mu - r^f) \geq \frac{\alpha\zeta\sigma_\epsilon^2}{1-\rho}$. The second inequality in turn arises from $\rho > -1$. As a result, this implies that

$$\psi_2^{(a),s} \geq \frac{1}{(1-\omega\delta)r^m w}\,,$$

which violates condition (2.7.6) derived above to satisfy statement (b). As a result, we only keep $\psi_1^{(a),s}$ as possible upper bound.

The upper bound for a global maximum, i.e. $\overline{\psi}^{GM,s}$, is given under Assumption 3 by

$$\begin{aligned}\overline{\psi}^{GM,s} &= \frac{2\sigma}{\zeta\theta(\mu-r^f)^2\sigma_\epsilon^2}\left(\sigma(\mu-r^f)(\rho-1)+\sqrt{\sigma^2(\mu-r^f)^2(\rho-1)^2+\sigma^2(\mu-r^f)^2(1-\rho^2)}\right)\\ &= \frac{2\sigma}{\zeta\theta(\mu-r^f)^2\sigma_\epsilon^2}\left(\sigma(\mu-r^f)(\rho-1)+\sigma(\mu-r^f)\sqrt{2(1-\rho)}\right)\\ &= \frac{2\sigma^2}{\zeta\theta(\mu-r^f)\sigma_\epsilon^2}\left(\sqrt{2(1-\rho)}-(1-\rho)\right).\end{aligned}$$

It is straightforward to see that $\overline{\psi}^{GM,s}$ is strictly positive as $\sqrt{(1-\rho)}\left(\sqrt{2}-\sqrt{1-\rho}\right)$ is strictly positive due to $\rho > -1$. As a result, Lemma 3 follows by the upper bound (2.7.6) and defining

$$\overline{\psi} \equiv \min\{\overline{\psi}^{GM,s}, \overline{\psi}_1^{(a),s}, \overline{\psi}^{(b),s}\}\ . \tag{2.7.7}$$

Notice that in the particular case of $\rho = \frac{1}{2}$, the conditions of statement (a) of Lemma 6 are satisfied such that $\Phi(\psi)$ is an affine function in $\mathbb{R}_+$ such that $\overline{\psi}^{GM,s}$ is not a restriction and $\overline{\psi} \equiv \min\{\overline{\psi}_1^{(a),s}, \overline{\psi}^{(b),s}\}$ applies. □

Proof Lemma 5.

To determine the initial distribution of terminal period equity e_i' from the perspective of bankers when determining their portfolio choices, we proceed in two steps: First, we solve for the entrepreneurs maximization problem to determine the gross capital returns from production. Second, we solve for the Nash bargaining outcome.

Proof. Part I: Entrepreneurial Problem

To begin with, entrepreneurs in country i maximize profits Π_i

$$\max_{\{l_i,k_i\}} \Pi_i(l_i,k_i) = A_i k_i l_i^{\xi} - w l_i - R_i k_i\ . \tag{2.7.8}$$

The corresponding first order condition with respect to labor reads $\xi A_i k_i l_i^{\xi-1} = w$. Hence, the profits accruing from physical capital are given by

$$\Pi_i(k_i) = (1-\xi)\, A_i k_i l_i^{\xi} - R_i k_i = \left[(1-\xi)A_i l_i^{\xi} - R_i\right] k_i \tag{2.7.9}$$

As labor is supplied inelastically and equals unity, we obtain that $R_{ii} = (1-\xi)z_i$, due to symmetry respectively $R_{ij} = (1-\xi)z_j$.

Part II: Bargaining Problem

We denote the total surplus of the match between a banker and an entrepreneur by $\mathcal{S}$. It is composed out of two components, the banker surplus $\mathcal{S}^b$ and the entrepreneurial surplus $\mathcal{S}^e$. For an investment in country i, the former is given by $\mathcal{S}^b_{ii} = R^l_{ii} - R^f$. This is due to the fact, that we implicitly assume that the banker has sufficiently large funds at her disposal to satisfy her optimal choices for both risky assets. As a result, her outside opportunity is characterized by risk free central bank reserve holdings with pay off R^f. Similarly, the entrepreneurial outside option is to not produce such that her surplus is $S^e_{ii} = R_{ii} - R^l_{ii}$. The Nash bargaining problem is then written as

$$\max_{\{R^l_{ii}\}} \left(R^l_{ii} - R^f\right)^{\theta} \left(R_{ii} - R^l_{ii}\right)^{1-\theta} \quad , \quad s.t. \quad \mathcal{S} \equiv R_{ii} - R^f \; . \tag{2.7.10}$$

As standard, the first order condition to the bargaining problem (2.7.10) is given by

$$\theta \left(R^l_{ii} - R^f\right)^{\theta-1} \left(R_{ii} - R^l_{ii}\right)^{1-\theta} = (1-\theta) \left(R^l_{ii} - R^f\right)^{\theta} \left(R_{ii} - R^l_{ii}\right)^{-\theta} \; .$$

The previous equation can be rewritten as $\theta\mathcal{S} = R^l_{ii} - R^f$ and $(1-\theta)\mathcal{S} = R_{ii} - R^l_{ii}$. It is also standard and straightforward to verify the second order condition. As a result, we obtain

$$R^l_{ii} = \theta(R_{ii} - R^f) + R^f = \theta\big((1-\xi)z_i - R^f\big) + R^f \; , \tag{2.7.11}$$

and by symmetry considerations analogously

$$R^l_{ij} = \theta(R_{ij} - R^f) + R^f = \theta\big((1-\xi)z_j - R^f\big) + R^f \; . \tag{2.7.12}$$

Having equations (2.7.11) and (2.7.12) at hands, we can state terminal period equity e'_i as

$$\begin{aligned}
e'_i &= R^l_{ii}k_{ii} + \Big(R^l_{ij} + \epsilon_j\left(1 - \mathcal{P}(m, k_{ij})\right)\Big)k_{ij} + R^f b_i - R^d d_i - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}'_i) \\
&= R^l_{ii}k_{ii} + \Big(R^l_{ij} + \epsilon_j\left(1 - \mathcal{P}(m, k_{ij})\right)\Big)k_{ij} + R^f\left(d_i + e_i - k_{ii} - k_{ij}\right) - R^d d_i - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}'_i) \\
&= R^f e_i + (R^l_{ii} - R^f)k_{ii} + \big(R^l_{ij} - R^f + \epsilon_j\left(1 - \mathcal{P}(m, k_{ij})\right)\big)k_{ij} + (R^f - R^d)d_i - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}'_i) \\
&\approx R^f e_i + \theta(r^l_{ii} - r^f)k_{ii} + \Big(\theta(r^l_{ij} - r^f) + \epsilon_j\left(1 - \mathcal{P}(m, k_{ij})\right)\Big)k_{ij} + (1-\omega)r^f d_i - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}'_i) \; ,
\end{aligned}$$

where r^f denotes the net monetary policy rate, respectively (r^l_{ii}, r^l_{ij}) net asset rates. The latter two are defined by $r^l_{ii} \equiv (1-\xi)z_i - 1$, respectively $r^l_{ij} \equiv (1-\xi)z_j - 1$. The second equality follows from a substitution of the initial period budget constraint. The third equation collects terms whereas the final equation makes use of a first order Taylor approximation around $r^f = 0$ such that $r^d \approx \omega r^f$ follows. We denote mean and variances of net asset rates by

$$\mu_i \equiv (1-\xi)\mu_{z_i} - 1\,, \qquad \sigma^2(r^l_{ii}) \equiv (1-\xi)^2\sigma^2_{z_i}\,, \tag{2.7.13}$$

$$\mu_j \equiv (1-\xi)\mu_{z_j} - 1\,, \qquad \sigma^2(r^l_{ij}) \equiv (1-\xi)^2\sigma^2_{z_j}\,. \tag{2.7.14}$$

Under Assumption 4, it is then evident that terminal equity follows a Normal distribution with mean

$$\mu_{e'_i} = (1+r^f)e_i + \theta\big(\mu_i - r^f\big)k_{ii} + \theta\big(\mu_j - r^f\big)k_{ij} + (1-\omega)r^f d_i - \mathcal{C}(m, k_{ij}, \Delta\tilde{e}'_i) \tag{2.7.15}$$

and variance

$$\sigma^2_{e'_i} = \sigma^2_i k^2_{ii} + \left(\sigma^2_j + \sigma^2_\epsilon \left(1 - \mathcal{P}(m, k_{ij})\right)^2\right)k^2_{ij} + 2\rho\sigma_i\sigma_j k_{ii}k_{ij}\,, \tag{2.7.16}$$

which completes the derivation of Lemma 5. □

Proof Lemma 6.

Proof. First, let us define the set Ω of auxiliary parameters by

$$\Omega \equiv \{\theta, \zeta_i, \mu_i, \mu_j, \sigma_i, \sigma_j, \sigma_\epsilon, \rho, r^m\}\,.$$

The auxiliary function (2.7.31) is given by

$$\Phi(\psi, \Omega) = 1 - \frac{1}{\sigma^2_i}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma^2_\epsilon\right)^2}{\sigma^2_j - \zeta_i\psi\theta(\mu_j - r^m)\sigma^2_\epsilon}\,. \tag{2.7.17}$$

To start with, three properties of $\Phi(\psi, \Omega)$ are evident:

(i) $\Phi(0, \Omega) = 1 - \rho^2 > 0$.

(ii) $\Phi(\infty, \Omega) = \infty$ and $\Phi(-\infty, \Omega) = -\infty$.

(iii) $\Phi(\psi, \Omega)$ is discontinuous at the point $\psi^{dc} = \frac{\sigma^2_j}{\zeta_i\theta(\mu_j - r^m)\sigma^2_\epsilon}$.

The second property follows from a straightforward application of L'Hôpital's rule, i.e.

$$\lim_{\psi\to\pm\infty}\Phi(\psi,\Omega) = 1 - \lim_{\psi\to\pm\infty}\frac{1}{\sigma_i^2}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma_\epsilon^2\right)\zeta_i\theta(\mu_i - r^m)\sigma_\epsilon^2}{\zeta_i\theta(\mu_j - r^m)\sigma_\epsilon^2}\,.$$

To show part (a) of Lemma 6, one can rewrite equation (2.7.17) as

$$\begin{aligned}\Phi(\psi,\Omega) &= 1 - \frac{1}{\sigma_i^2}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2}\\ &= 1 - \frac{1}{4}\left(\frac{\mu_i - r^m}{\mu_j - r^m}\right)^2\frac{1}{\sigma_i^2}\frac{\left(2\rho\sigma_i\sigma_j\frac{\mu_j - r^m}{\mu_i - r^m} - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2}\,.\end{aligned}$$

The terminal ratio cancels if $2\rho\sigma_i\sigma_j\frac{\mu_j - r^m}{\mu_i - r^m} = \sigma_j^2$, which can be rearranged to $2\rho\frac{\mu_j - r^m}{\sigma_j} = \frac{\mu_i - r^m}{\sigma_i}$. If the former condition applies, we can rewrite equation (2.7.17) as

$$\Phi(\psi,\Omega) = 1 - \frac{1}{4}\left(\frac{\mu_i - r^m}{\mu_j - r^m}\right)^2\frac{1}{\sigma_i^2}\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2\right)\,.$$

The previous function is affine in ψ, strictly increasing and weakly positive on Ψ_+ if the condition $2\frac{\sigma_i}{\sigma_j} \geq \frac{\mu_i - r^m}{\mu_j - r^m}$ applies.

To show in turn part (b) of Lemma 6, recognize that equation (2.7.17) is nonlinear in ψ in the case of $2\rho\frac{\mu_j - r^m}{\sigma_j} \neq \frac{\mu_i - r^m}{\sigma_i}$. The roots of this functional are consequently characterized by

$$\begin{aligned}&\sigma_i^2\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_i^2\sigma_\epsilon^2 - \left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma_\epsilon^2\right)^2 = 0\\ \Leftrightarrow &\underbrace{-\left(\frac{1}{2}\zeta_i\theta(\mu_i - r^m)\sigma_\epsilon^2\right)^2}_{\equiv\mathcal{A}}\psi^2 + \underbrace{\zeta_i\theta\sigma_i\sigma_\epsilon^2\left(\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)\right)}_{\equiv\mathcal{B}}\psi + \underbrace{(1-\rho^2)\sigma_i^2\sigma_j^2}_{\equiv\mathcal{C}} = 0\,.\end{aligned}$$

The solutions $\psi_{1,2}$ to the previous equation are given by

$$\Gamma\left(\left[\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)\right] \pm \sqrt{\left[\rho\sigma_j(\mu_i - r^m) - \sigma_i(\mu_j - r^m)\right]^2 + (\mu_i - r^m)^2(1-\rho^2)\sigma_j^2}\right)$$

where $\Gamma \equiv \frac{2\sigma_i}{\zeta_i\theta\sigma_\epsilon^2(\mu_i - r^m)^2}$ denotes a strictly positive constant. Let us denote by ψ_1 the larger of the two solutions. It is hence evident that ψ_1 strictly positive as long as $\rho \notin \{-1, 1\}$. Notice that equation (2.7.17) is strictly larger than unity if $\psi > \psi^{dc}$. As a result, we have $\psi_2 < 0 < \psi_1 < \psi^{dc}$. Denoting $\overline{\psi} \equiv \psi_1$ completes the proof of part (b) of Lemma 6. □

Proof Lemma 7.

Proof. From equation (2.7.3) in the proof of Lemma 1, we know that the optimal risk management activity is given by

$$m^* = \left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{1}{\chi+2\varphi}} c_i^{-\frac{\lambda}{\chi+2\varphi}} \left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}} \equiv \Phi\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}} ,$$

where we have defined the auxiliary parameter $\Phi \equiv \left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{1}{\chi+2\varphi}} c_i^{-\frac{\lambda}{\chi+2\varphi}} > 0$. Additionally, expected bank profitability before cost management is given by

$$\begin{aligned}\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right] &= r^f e_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} + (1-\omega)r^f d_i \\ &= \left[1-\delta+(1-\omega)\delta\right] r^f w_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} \,.\end{aligned}$$

The first order condition of optimal risk management with respect to cross border investment is given by

$$\frac{\partial m^*}{\partial k_{ij}} = \Phi\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}} \left(\frac{\lambda}{\chi+2\varphi}\frac{\psi\theta(\mu_j-r^f)}{1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]} + \frac{2(1+\eta)-\nu}{\chi+2\varphi}\frac{1}{k_{ij}}\right)$$

Under part (a) of Assumption 4 we have that $\frac{\lambda}{\chi+2\varphi} > 0$, as well as $\frac{2(1+\eta)-\nu}{\chi+2\varphi} > 0$ due to $\nu \in [0,1)$. Hence, $\frac{\partial m^*}{\partial k_{ij}} > 0$ and the first statement of Lemma 7 follows.

To show the shape of optimal management activities in cross border investment, we proceed by checking the sign of the second derivative. Using the the first order condition from above, we obtain

$$\begin{aligned}\frac{\partial^2 m^*}{\partial k_{ij}^2} =& \Phi\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}} \left(\frac{\lambda}{\chi+2\varphi}\frac{\psi\theta(\mu_j-r^f)}{1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]} + \frac{2(1+\eta)-\nu}{\chi+2\varphi}\frac{1}{k_{ij}}\right)^2 \\ &+ \Phi\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}} \left(\frac{\lambda}{\chi+2\varphi}\frac{\psi^2\theta^2(\mu_j-r^f)^2}{\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^2} - \frac{2(1+\eta)-\nu}{\chi+2\varphi}\frac{1}{k_{ij}^2}\right)\end{aligned}$$

As $m^* > 0$, to establish concavity the following inequality has to hold

$$-\frac{\lambda}{\chi+2\varphi}\frac{\psi^2\theta^2(\mu_j-r^f)^2}{\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]\right)^2} + \frac{2(1+\eta)-\nu}{\chi+2\varphi}\frac{1}{k_{ij}^2} \geq \left(\frac{\lambda}{\chi+2\varphi}\frac{\psi\theta(\mu_j-r^f)}{1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]} + \frac{2(1+\eta)-\nu}{\chi+2\varphi}\frac{1}{k_{ij}}\right)^2 .$$

The previous equation can be restated in the following form

$$-\Xi_1 x^2 + \Xi_2 y^2 \geq (\Xi_1 x + \Xi_2 y)^2 \ ,$$

where we have used the definitions $\Xi_1 \equiv \frac{\lambda}{\chi+2\varphi}, \Xi_2 \equiv \frac{2(1+\eta)-\nu}{\chi+2\varphi}, x \equiv \frac{\psi\theta(\mu_j - r^f)}{1-\psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}$ and $y = \frac{1}{k_{ij}}$. Redefining $r \equiv \frac{y}{x}$, we can state for values $\psi > 0$ that

$$-\Xi_1 + \Xi_2 r^2 \geq (\Xi_1 + \Xi_2 r)^2 \ , \tag{2.7.18}$$

which can be rewritten as

$$\Xi_2(1-\Xi_2)r^2 - 2\Xi_1\Xi_2 r - \Xi_1(1+\Xi_1) \geq 0 \ . \tag{2.7.19}$$

Due to part (a) of Assumption 4, it is evident that $\Xi_1 > 0$. Subsequently, we also show that the aforementioned assumption implies that $0 < \Xi_2 < 1$. If this condition would not apply, i.e. in the case of $\Xi_2 \leq 0$ or $\Xi_2 \geq 1$, equation (2.7.18) would never hold and optimal risk management activity was a strictly convex function in cross border asset investment. To begin with, under part (a) of Assumption 4 $\Xi_2 > 0$ as $\nu \in [0, 1)$. To verify the upper limit, suppose that

$$\frac{2(1+\eta)-\nu}{\chi+2\varphi} \geq 1 \Leftrightarrow 2(1+\eta)-\nu \geq \chi + 2\varphi = \frac{2\varphi(1-\nu)}{1+2\eta} + 2\varphi \ ,$$

where the last equality follows from a substitution for χ from part (a) of Assumption 4. Simplifying the right hand side, we finally arrive at

$$2(1+\eta)-\nu \geq 2\varphi\frac{2(1+\eta)-\nu}{1+2\eta} \Leftrightarrow 1 \geq \frac{2\varphi}{1+2\eta} \ .$$

Together with the assumption on the lower bound of φ from the proof of Lemma **??** this implies

$$\frac{1}{1-\nu}\left(\frac{1}{2}+\eta\right) < \varphi < \frac{1}{2}+\eta \ ,$$

which is a contradiction. As a result, we conclude that $\Xi_2 < 1$. Additionally, also recognize that we obtain an upper bound of unity for Ξ_1 as

$$\Xi_1 = \frac{\lambda}{\chi + 2\varphi} = \frac{1}{2\varphi} < \frac{1-\nu}{1+2\eta} < 1 \,.$$

The second equality follows directly from part (a) of Assumption 4 by substituting $\lambda = \frac{\chi+2\varphi}{2\varphi}$. The first strict inequality follows by substituting in for φ its lower bound $\underline{\varphi} = \frac{1+2\eta}{2(1-\nu)}$, while the terminal strict inequality follows in turn from $\eta > 0$ and $\nu \in [0,1)$. As a result, part (a) of Assumption 4 imposes that $0 < \Xi_1 < 1$ and $0 < \Xi_2 < 1$.

Having the previous inequality at hands, we can then analyze the properties of the sign of the second derivative in equation (2.7.19). Due to $0 < \Xi_2 < 1$, it follows that the left hand side of (2.7.19) is a strictly convex function in r with minimum at $r^{min} = \frac{\Xi_1}{1-\Xi_2} > 0$. For all $r < r^{min}$ the left hand side of (2.7.19) strictly decreases in r, whereas for all $r > r^{min}$ it strictly increases. The left hand side takes a negative value at r^{min} as

$$\Xi_2(1-\Xi_2)\frac{\Xi_1^2}{(1-\Xi_2)^2} - 2\Xi_1\Xi_2\frac{\Xi_1}{1-\Xi_2} - \Xi_1(1+\Xi_1) = -\frac{\Xi_1^2\Xi_2}{1-\Xi_2} - \Xi_1(1+\Xi_1) < 0 \,.$$

Additionally, the left hand side of (2.7.19) is strictly negative at $r = 0$. We conclude that the left hand side is strictly positive for all $r > r_0^+$, where r_0^+ denotes the positive root to the left hand side of (2.7.19). It is given by

$$\begin{aligned} r_0^+ &= \frac{1}{2\Xi_2(1-\Xi_2)}\left(2\Xi_1\Xi_2 + \sqrt{4\Xi_1^2\Xi_2^2 + 4\Xi_2(1-\Xi_2)\Xi_1(1+\Xi_1)}\right) \\ &= \frac{\Xi_1}{1-\Xi_2}\left(1 + \sqrt{1 + \frac{(1+\Xi_1)(1-\Xi_2)}{\Xi_1\Xi_2}}\right) > r^{min} \,. \end{aligned}$$

Finally, we conclude that optimal risk management activities are strictly concave for $r > r_0^+$ and strictly convex for $r < r_0^+$, i.e. m^* has a turning point at r_0^+. Resubstitution for r gives

$$r = \frac{1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}{\psi\theta(\mu_j - r^f)k_{ij}} > r_0^+ \,.$$

As the left hand side of the previous equation is strictly decreasing in k_{ij} with limit infinity, we conclude that there exists a $\tilde{k}_{ij}$ below which m^* is strictly concave in k_{ij}, respectively above which it is strictly convex in k_{ij}. Finally, we have to check whether values of k_{ij} above the threshold value $\tilde{k}_{ij}$ are feasible. Due to the positivity of the risk management costs, we obtain an explicit upper limit by

$$1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right] \geq 0 \Leftrightarrow k_{ij}^{max} = \frac{1 - \psi\left[(1-\omega\delta)r^f w_i + \theta(\mu_i - r^f)k_{ii}\right]}{\psi\theta(\mu_j - r^f)} \ .$$

In turn, the threshold value of the turning point is characterized by

$$\frac{1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right]}{\psi\theta(\mu_j - r^f)\tilde{k}_{ij}} = r_0^+ \Leftrightarrow \tilde{k}_{ij} = \frac{1 - \psi\left[(1-\omega\delta)r^f w_i + \theta(\mu_i - r^f)k_{ii}\right]}{\psi\theta(\mu_j - r^f)(1 + r_0^+)} \ .$$

As $r_0^+ > 0$, we conclude that $\tilde{k}_{ij} < k_{ij}^{max}$ such that optimal risk management activity m^* always has a concave as well as a convex subspace in cross border investment k_{ij}.

Finally, in the case of $\psi = 0$, it is evident that m^* is a strictly increasing and concave function in k_{ij} as $x = 0$ in this case, and additionally $0 < \Xi_2 < 1$ holds. This concludes the proof of Lemma 7. □

Proof of Equivalence of Maximization Problems.

Proof. To prove the equivalence result, we show the equality of first order conditions for both objectives (P1) and (P1′). We start out with the latter problem. Terminal equity under problem (P1′) is given by

$$\begin{aligned} e_i' &= R_{ii}^l k_{ii} + R_{ij}^l k_{ij} + R^m b_i - R^d d_i \\ &= R_{ii}^l k_{ii} + R_{ij}^l k_{ij} + R^m(d_i + e_i - k_{ii} - k_{ij}) - R^d d_i \\ &= (1 + r^f)e_i + \theta(r_{ii}^l - r^f)k_{ii} + \theta(r_{ij}^l - r^f)k_{ij} + (1-\omega)r^f d_i \ . \end{aligned}$$

As in Lemma 5, terminal equity is normally distributed with the following mean and variance

$$\begin{aligned} \mu_{e_i'} &= (1 + r^f)e_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} + (1-\omega)r^f d_i \ , \\ \sigma_{e_i'}^2 &= \sigma_i^2 k_{ii}^2 + \left(\sigma_j^2 + \zeta_i\left(1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)\frac{1}{k_{ij}}\sigma_\epsilon^2\right)k_{ij}^2 + 2\rho\sigma_i\sigma_j k_{ii}k_{ij} \ . \end{aligned}$$

Additionally, expected bank profitability is given by

$$\mathbb{E}\left[\Delta\tilde{e}_i'|\mathcal{I}\right] = \left[1 - \delta + (1-\omega)\delta\right]r^f w_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} \ .$$

Following the standard routine, the objective function of bankers writes under the CARA-

Normal framework as

$$\max_{\{k_{ii},k_{ij},b_i\}} \mathbb{E}\left[u(e_i')|\mathcal{I}\right] = -\frac{1}{\alpha}e^{-\alpha(\mu_{e_i'}-\frac{1}{2}\alpha\sigma^2_{e_i'})}\ . \tag{2.7.20}$$

FOC's Problem (P1′). The first order conditions to (2.7.20) are given by

$$\{k_{ii}\}\ -\alpha\theta(\mu_i - r^f) + \frac{1}{2}\alpha^2\left[2\sigma_i^2 k_{ii} - \zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2 k_{ij} + 2\rho\sigma_i\sigma_j k_{ij}\right] = 0\ ,$$
$$\{k_{ij}\}\ -\alpha\theta(\mu_j - r^f) + \frac{1}{2}\alpha^2\left[2\sigma_j^2 k_{ij} - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 k_{ij} + \zeta_i\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)\sigma_\epsilon^2 + 2\rho\sigma_i\sigma_j k_{ii}\right] = 0\ .$$

Rearranging the previous equations results in

$$k_{ii} = \frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{k_{ij}}{\sigma_i^2}\left[\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right]\ , \tag{2.7.21}$$

$$k_{ij} = \frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - k_{ii}\frac{\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} - \frac{\zeta_i}{2}\frac{\sigma_\epsilon^2\left(1-\psi(1-\omega\delta)r^f w_i\right)}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\ . \tag{2.7.22}$$

FOC's Problem (P1). With respect to problem (P1), let us first restate the distribution of terminal equity derived in Lemma 5. It follows a Normal distribution with mean and variance

$$\mu_{e_i'} = (1-r^f)e_i + \theta(\mu_i - r^f)k_{ii} + \theta(\mu_j - r^f)k_{ij} + (1-\omega)r^f d_i - \frac{1}{\chi}c_i^\lambda\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^\lambda m^\chi k_{ij}^\nu\ ,$$
$$\sigma^2_{e_i'} = \sigma_i^2 k_{ii}^2 + \sigma_j^2 k_{ij}^2 + \sigma_\epsilon^2 m^{-2\varphi} k_{ij}^{2(1+\eta)} + 2\rho\sigma_i\sigma_j k_{ii}k_{ij}\ .$$

The first order condition w.r.t. domestic investment k_{ii} is given by

$$-\alpha\theta(\mu_i - r^f) - \alpha\psi\theta(\mu_i - r^f)\frac{\lambda}{\chi}c_i^\lambda\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda-1} m^\chi k_{ij}^\nu + \frac{1}{2}\alpha^2\left[2\sigma_i^2 k_{ii} + 2\rho\sigma_i\sigma_j k_{ij}\right] = 0\ . \tag{2.7.23}$$

Correspondingly, the first order condition w.r.t. cross border investment k_{ij} is given by

$$-\alpha\theta(\mu_j - r^f) - \alpha\psi\theta(\mu_j - r^f)\frac{\lambda}{\chi}c_i^\lambda\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda-1} m^\chi k_{ij}^\nu + \alpha\frac{\nu}{\chi}c_i^\lambda\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^\lambda m^\chi k_{ij}^{\nu-1}$$
$$+\frac{1}{2}\alpha^2\left[2\sigma_j^2 k_{ij} + 2(1+\eta)\sigma_\epsilon^2 m^{-2\varphi}k_{ij}^{1+2\eta} + 2\rho\sigma_i\sigma_j k_{ii}\right] = 0\ . \tag{2.7.24}$$

Finally, optimal risk management is characterized by

$$\alpha c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda} m^{\chi-1}k_{ij}^{\nu}-\alpha^2\varphi\sigma_\epsilon^2 m^{-2\varphi-1}k_{ij}^{2(1+\eta)}=0\ . \tag{2.7.25}$$

The first order condition with respect to optimal risk management activity m results in the optimal monitoring effort (2.7.3)

$$m^*=\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{1}{\chi+2\varphi}}c_i^{-\frac{\lambda}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{-\frac{\lambda}{\chi+2\varphi}}k_{ij}^{\frac{2(1+\eta)-\nu}{\chi+2\varphi}}$$

Based on the previous equation we obtain

$$\begin{aligned}
&\alpha\psi\theta(\mu_i-r^f)\frac{\lambda}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda-1}m^{\chi}k_{ij}^{\nu}\\
=&\alpha\psi\theta(\mu_i-r^f)\frac{\lambda}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda-1}\left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}}c_i^{-\frac{\lambda\chi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{-\frac{\lambda\chi}{\chi+2\varphi}}k_{ij}^{\frac{2(1+\eta)\chi-\nu\chi+(\chi+2\varphi)\nu}{\chi+2\varphi}}\\
=&\alpha\psi\theta(\mu_i-r^f)\frac{\lambda}{\chi}\left(\alpha\varphi\right)^{\frac{\chi}{\chi+2\varphi}}\sigma_\epsilon^2 c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}-1}k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}}\\
=&\alpha\psi\theta(\mu_i-r^f)\frac{\lambda}{\chi}\left(\alpha\varphi\right)^{\frac{\chi}{\chi+2\varphi}}\sigma_\epsilon^2 c_i k_{ij}\ ,
\end{aligned}$$

where the last equality follows from Assumption 4 (a). The previous equation can be rewritten such that

$$\begin{aligned}
\alpha\psi\theta(\mu_i-r^f)\frac{\lambda}{\chi}\left(\alpha\varphi\right)^{\frac{\chi}{\chi+2\varphi}}\sigma_\epsilon^2 c_i k_{ij}&=\alpha^2\psi\theta(\mu_i-r^f)\frac{\lambda\varphi}{\chi}\left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}}\sigma_\epsilon^2 c_i k_{ij}\\
&=\alpha^2\psi\theta(\mu_i-r^f)\frac{\chi+2\varphi}{2\chi}\left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}}c_i\sigma_\epsilon^2 k_{ij}\\
&=\frac{1}{2}\alpha^2\zeta_i\psi\theta(\mu_i-r^f)\sigma_\epsilon^2 k_{ij}\ .
\end{aligned}$$

As a result, equation (2.7.23) writes

$$-\alpha\theta(\mu_i-r^f)+\frac{1}{2}\alpha^2\left[2\sigma_i^2 k_{ii}-\zeta_i\psi\theta(\mu_i-r^f)\sigma_\epsilon^2 k_{ij}+2\rho\sigma_i\sigma_j k_{ij}\right]=0\ ,$$

and thus corresponds to the first order condition of problem (P1′). In a similar spirit, we obtain

$$\alpha\psi\theta(\mu_j-r^f)\frac{\lambda}{\chi}c_i^{\lambda}\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda-1}m^{\chi}k_{ij}^{\nu}=\frac{1}{2}\alpha^2\zeta_i\psi\theta(\mu_j-r^f)\sigma_\epsilon^2 k_{ij}$$

Additionally, we have

$$
\begin{aligned}
&\alpha \frac{\nu}{\chi} c_i^{\lambda} \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda} m^{\chi} k_{ij}^{\nu-1} \\
=&\alpha \frac{\nu}{\chi} c_i^{\lambda} \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right)^{\lambda} \left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}} c_i^{-\frac{\lambda\chi}{\chi+2\varphi}} \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right)^{-\frac{\lambda\chi}{\chi+2\varphi}} k_{ij}^{\frac{2(1+\eta)\chi-\nu\chi+(\nu-1)(\chi+2\varphi)}{\chi+2\varphi}} \\
=&\alpha \frac{\nu}{\chi} \left(\alpha\varphi\sigma_\epsilon^2\right)^{\frac{\chi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}} \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{\frac{2[(1+\eta)\chi+\varphi\nu]}{\chi+2\varphi}-1} \\
=&\alpha^2 \frac{\nu\varphi}{\chi} \left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2
\end{aligned}
$$

Finally, we obtain

$$
\begin{aligned}
&\alpha^2(1+\eta)\sigma_\epsilon^2 m^{-2\varphi} k_{ij}^{1+2\eta} \\
=&\alpha^2(1+\eta)\sigma_\epsilon^2 \left(\alpha\varphi\sigma_\epsilon^2\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i^{\frac{2\lambda\varphi}{\chi+2\varphi}} \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right)^{\frac{2\lambda\varphi}{\chi+2\varphi}} k_{ij}^{-2\varphi\frac{2(1+\eta)-\nu}{\chi+2\varphi}} k_{ij}^{1+2\eta} \\
=&\alpha^2(1+\eta) \left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2 k_{ij}^{\frac{-4(1+\eta)\varphi+2\varphi\nu+(1+2\eta)(\chi+2\varphi)}{\chi+2\varphi}} \\
=&\alpha^2(1+\eta) \left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2 \,,
\end{aligned}
$$

where the last equality follows from Assumption 4. Combining the previous two terms, we thus obtain

$$
\begin{aligned}
&\alpha^2 \frac{\nu\varphi+(1+\eta)\chi}{\chi} \left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2 = \alpha^2 \frac{\chi+2\varphi}{2\chi} \left(\alpha\varphi\right)^{-\frac{2\varphi}{\chi+2\varphi}} c_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2 \\
=&\frac{1}{2}\alpha^2 \zeta_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2
\end{aligned}
$$

As a result, equation (2.7.24) writes as

$$
-\alpha\theta(\mu_j - r^f) + \frac{1}{2}\alpha^2 \left[2\sigma_j^2 k_{ij} - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 k_{ij} + \zeta_i \left(1-\psi \mathbb{E}\left[\Delta \tilde{e}_i{}'|\mathcal{I}\right]\right) \sigma_\epsilon^2 + 2\rho\sigma_i\sigma_j k_{ii}\right] = 0 \,,
$$

which corresponds in turn to the first order condition of problem (P1′). □

Proof: Corollary

Proof Corollary 2.

Proof. The inverse bank risk managing ability ζ_i under Assumption 4 (a) is given by

$$\zeta_i = \frac{2(1+\eta)-\nu}{1-\nu} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i \,.$$

Thus, it is straightforward to see that $\frac{\partial \zeta_i}{\partial \alpha} < 0$, $\frac{\partial \zeta_i}{\partial \varphi} < 0$, and $\frac{\partial \zeta_i}{\partial c_i} > 0$ given $\nu \in [0,1)$ and $\eta > 0$. To derive the partial derivative with respect to the elasticities (η, ν), we first restate the initial equation as

$$\zeta_i = \frac{2(1+\eta)-\nu}{1-\nu} e^{-\frac{1+2\eta}{2(1+\eta)-\nu}\ln\alpha} e^{-\frac{1+2\eta}{2(1+\eta)-\nu}\ln\varphi} c_i \,.$$

As a result, we obtain

$$\begin{aligned}\frac{\partial \zeta_i}{\partial \eta} =& \frac{2}{1-\nu} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i + \frac{2(1+\eta)-\nu}{1-\nu} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i \left[-\frac{2\left(2(1+\eta)-\nu\right)-2(1+2\eta)}{(2(1+\eta)-\nu)^2}\ln\alpha\right] \\ &+ \frac{2(1+\eta)-\nu}{1-\nu} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i \left[-\frac{2\left(2(1+\eta)-\nu\right)-2(1+2\eta)}{(2(1+\eta)-\nu)^2}\ln\varphi\right] \,.\end{aligned}$$

The sign of the previous equation is positive if

$$2 - \frac{2(1-\nu)}{2(1+\eta)-\nu} \ln(\alpha\varphi) \geq 0 \,.$$

The above condition is satisfied if

$$\eta \geq \underline{\eta} \equiv \frac{\nu + (1-\nu)\ln(\alpha\varphi)}{2} - 1 \,.$$

Similarly, we obtain

$$\frac{\partial \zeta_i}{\partial \nu} = \frac{1+2\eta}{(1-\nu)^2} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i + \frac{2(1+\eta)-\nu}{1-\nu} (\alpha\varphi)^{-\frac{1+2\eta}{2(1+\eta)-\nu}} c_i \left[\frac{1+2\eta}{(2(1+\eta)-\nu)^2}\ln(\alpha\varphi)\right] \,.$$

The sign of the previous equation is positive if

$$\frac{1+2\eta}{1-\nu} + \frac{1+2\eta}{2(1+\eta)-\nu} \ln(\alpha\varphi) \geq 0 \,.$$

The above condition is satisfied if

$$\nu\left(1+\ln(\alpha\varphi)\right) \leq \ln(\alpha\varphi) + 2(1+\eta)$$

If $\ln(\alpha\varphi) \geq -2(1+\eta)$, the previous inequality is always satisfied as $\nu \in [0,1)$. On the contrary, if $\ln(\alpha\varphi) < -2(1+\eta)$, the inequality can be rewritten as

$$\nu \geq \underline{\nu} \equiv \frac{2(1+\eta) + \ln(\alpha\varphi)}{1+\ln(\alpha\varphi)} .$$

The right hand side of the previous equation is strictly decreasing in $\ln(\alpha\varphi)$ and takes values on $(0,1)$, such that $\frac{\partial\zeta_i}{\partial\nu} \geq 0$ if $\nu \geq \underline{\nu}$. This completes the proof of Corollary 2. □

Proof Corollary 5.

Proof. The proof follows in two steps. In the first part, we derive the effects of monetary policy on home bias fluctuations in case that the expected profitability channel is absent. In the second part, we analyse the effects of monetary policy on home bias fluctuations in case of a removal of cross border information frictions.

Part I: Bank home bias without profitability channel.
From equations (2.7.33) and (2.7.34) in the main body of the text, it is straightforward to see, that optimal bank lending decisions of country i bankers are characterized in the absence of a expected profitability channel ($\psi = 0$) by

$$k_{ii} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \rho\frac{\sigma_j}{\sigma_i}\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} + \frac{1}{2}\rho\frac{\sigma_j}{\sigma_i}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\right),$$

$$k_{ij} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right).$$

In a similar fashion, we obtain by an application of a symmetry argument for the lending decisions of bankers located in country j

$$k_{jj} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right),$$

$$k_{ji} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \rho\frac{\sigma_j}{\sigma_i}\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \frac{1}{2}\zeta_j\frac{\sigma_\epsilon^2}{\sigma_i^2}\right).$$

According to equation (2.2.6) home bias of country i in the model is given by

$$\mathcal{HB}_i = 1 - \frac{1+\frac{w_j}{w_i}}{1+\frac{k_{jj}}{k_{ij}}} \; . \tag{2.7.26}$$

The home bias measure is discontinuous at $\frac{k_{jj}}{k_{ij}} = -1$. For values $\frac{k_{jj}}{k_{ij}} > -1$, it increases in reaction to a parameter change if the ratio $\frac{k_{jj}}{k_{ij}}$ increases in the respective parameter. The expression is given by

$$\frac{k_{jj}}{k_{ij}} = \frac{\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}}{\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}} \; . \tag{2.7.27}$$

I. Loanable Wealth and Home Bias

It is straightforward to see that home bias (2.7.26) increases in the ratio of loanable wealth $\frac{w_j}{w_i}$.

II. Monetary Policy and Home Bias

The comparative statics of (2.7.27) with respect to the monetary policy rate are given by

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial r^f} = \frac{\left(-\frac{\theta}{\alpha\sigma_j^2}+\rho\frac{\sigma_i}{\sigma_j}\frac{\theta}{\alpha\sigma_i^2}\right)\left[\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right]-\left(-\frac{\theta}{\alpha\sigma_j^2}+\rho\frac{\sigma_i}{\sigma_j}\frac{\theta}{\alpha\sigma_i^2}\right)\left[\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}+\frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right]}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} \; .$$

The previous equation can be simplified to

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial r^f} = \frac{-\left(-\frac{\theta}{\alpha\sigma_j^2}+\rho\frac{\sigma_i}{\sigma_j}\frac{\theta}{\alpha\sigma_i^2}\right)\left[\frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}+\frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right]}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} = \frac{1}{2}\frac{\theta\sigma_\epsilon^2}{\alpha\sigma_j^4}\frac{\left(1-\rho\frac{\sigma_j}{\sigma_i}\right)\left[\zeta_i+\rho\zeta_j\frac{\sigma_j}{\sigma_i}\right]}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} \; .$$

The previous derivative is positive if both terms in the numerator are either positive or negative and at least one manageability parameter is unequal to zero and positive. The first condition is satisfied if

$$-\frac{\sigma_i}{\sigma_j}\frac{\zeta_i}{\zeta_j} \leq \rho \leq \frac{\sigma_i}{\sigma_j} \; .$$

The second condition does never apply as $\rho \geq \frac{\sigma_i}{\sigma_j}$ and $\rho \leq -\frac{\sigma_i}{\sigma_j}\frac{\zeta_i}{\zeta_j}$ cannot be jointly satisfied. Under the symmetry Assumption 3, the former condition reduces to $-1 \leq \rho \leq 1$, which always holds as it covers the entire support of ρ.

Special Case $\rho = 0$: In the case of zero correlation, home bias can be further simplified to

$$\mathcal{HB}_i = 1 - \frac{1 + \frac{w_j}{w_i}}{1 + \frac{1}{1 - \frac{1}{2}\frac{\alpha\zeta_i\sigma_\epsilon^2}{\theta(\mu_j - r^f)}}} \,.$$

III. Cross-Border Information Friction and Home Bias

The comparative statics of (2.7.26) with respect to cross border uncertainty are given by

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\sigma_\epsilon^2} = \frac{\frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j}{\sigma_i^2}\left[\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right] + \frac{1}{2}\frac{\zeta_i}{\sigma_j^2}\left[\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right]}{\left(\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} \,.$$

The sign of the former expression is consequently determined by

$$\text{sgn}\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\sigma_\epsilon^2} = \left[\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2}\right]\left(\frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j}{\sigma_i^2} + \frac{1}{2}\frac{\zeta_i}{\sigma_j^2}\right) \,. \tag{2.7.28}$$

The overall sign is weakly positive if the following correlation bounds apply

$$-\frac{\sigma_i}{\sigma_j}\frac{\zeta_i}{\zeta_j} \leq \rho \leq \frac{\mu_j - r^f}{\mu_i - r^f}\frac{\sigma_i}{\sigma_j} \,.$$

Under Assumption 3, the previous equality holds. If we also assume that (k_{jj}, k_{ij}) are weakly positive, the first component of the initial sign determining equation is strictly positive. The sign is thus pinned down by the second component. It is positive if the following inequality holds, which is obviously satisfied under Assumption 3:

$$\rho \geq -\frac{\zeta_i}{\zeta_j}\frac{\sigma_i}{\sigma_j} \,.$$

IV. Risk Management Ability and Home Bias

Let us assume that both investment positions (k_{jj}, k_{ij}) are weakly positive. It is straightforward to see from equation (2.7.27) that $\frac{k_{jj}}{k_{ii}}$ increases in ζ_i, and increases in ζ_j if $\rho \geq 0$, respectively decreases if $\rho < 0$. In case of a symmetric risk management ability, i.e., $\zeta \equiv \zeta_i = \zeta_j$, we have

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\sigma_\epsilon^2} = \frac{\frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\sigma_\epsilon^2}{\sigma_i^2}\left[\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta\frac{\sigma_\epsilon^2}{\sigma_j^2}\right] + \frac{1}{2}\frac{\sigma_\epsilon^2}{\sigma_j^2}\left[\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta\sigma_\epsilon^2}{\sigma_i^2}\right]}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} .$$

The sign of the previous derivative is determined by

$$\text{sgn}\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\sigma_\epsilon^2} = \frac{1}{2}\frac{\sigma_\epsilon^2}{\sigma_j^2}\left[\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}\right]\left(1+\rho\frac{\sigma_j}{\sigma_i}\right) . \tag{2.7.29}$$

The sign is weakly positive in turn if the following inequality applies

$$-\frac{\sigma_i}{\sigma_j} \leq \rho \leq \frac{\mu_j - r^f}{\mu_i - r^f}\frac{\sigma_i}{\sigma_j} ,$$

which is obviously satisfied if Assumption 3 is imposed.

V. Fundamental Asset Correlation and Home Bias

Finally, with respect to the asset correlation we obtain the comparative statics

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\rho} = \frac{-\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2}{\alpha\sigma_i^2}\left(\frac{\theta(\mu_j-r^f)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2} - \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\right) + \frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2}\left(\frac{\theta(\mu_j-r^f)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right)}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} .$$

The previous equation can be rearranged to

$$\begin{aligned}
\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\rho} &= \frac{-\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2}{\alpha\sigma_i^2}\left(-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2} - \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\right) + \frac{1}{2}\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\frac{\theta(\mu_j-r^f)}{\alpha\sigma_j^2} + \frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2}\left(-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2} + \frac{1}{2}\rho\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\right)}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} \\
&= \frac{-\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2}{\alpha\sigma_i^2}\left(-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2} - \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\right) + \frac{1}{2}\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\frac{\theta(\mu_j-r^f)}{\alpha\sigma_j^2} + \frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)}{\alpha\sigma_i^2}\left(-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2}{\alpha\sigma_i^2}\right)}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2} .
\end{aligned}$$

Collecting terms gives us finally

$$\frac{\partial\left(\frac{k_{jj}}{k_{ij}}\right)}{\partial\rho}=\frac{\frac{1}{2}\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2}{\alpha\sigma_i^2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}+\frac{1}{2}\frac{\sigma_i}{\sigma_j}\frac{\zeta_j\sigma_\epsilon^2}{\sigma_i^2}\frac{\theta(\mu_j-r^f)}{\alpha\sigma_j^2}}{\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\frac{1}{2}\zeta_i\frac{\sigma_\epsilon^2}{\sigma_j^2}\right)^2}\,.$$

The sign of the former expression is positive if

$$\left(\theta(\mu_i-r^f)-\frac{1}{2}\alpha\zeta_j\sigma_\epsilon^2\right)\zeta_i+\theta(\mu_j-r^f)\zeta_j>0\,. \tag{2.7.30}$$

This condition can be rewritten such that $\theta(\mu_i-r^f)\zeta_i+\left(\theta(\mu_j-r^f)-\frac{1}{2}\alpha\zeta_i\sigma_\epsilon^2\right)\zeta_j>0$. A sufficient condition for the former condition to hold is that there exists an adjusted (weakly) positive risk-premium for investments abroad, i.e. $\theta(\mu_j-r^f)-\frac{1}{2}\alpha\zeta_i\sigma_\epsilon^2>0$. In these cases, the correlation between home and foreign risky assets amplifies bank home bias through the manageability channel: The higher the correlation between both assets is, the more banks shift their portfolio towards the domestic risky asset in order to avoid the reduction in the risk premium which arises through to the additional manageable risk component. Notice, that the correlation between both assets is irrelevant for the bank home bias if both countries have perfect manageability, i.e. $\zeta_i=\zeta_j=0$. Under Assumption 3, the condition on the adjusted weakly positive risk premium after risk management activities remains obviously valid. This concludes the proof of statement (a) of Corollary 5.

Part II: Bank Home Bias Without Cross-Border Information Friction

From equations (2.7.33) and (2.7.34) in the main body of the text, it is straightforward to derive, that optimal bank lending decisions of country i bankers are characterized in the absence of cross-border information frictions ($\sigma_\epsilon^2=0$) by

$$k_{ii}=\frac{1}{1-\rho^2}\left(\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}-\rho\frac{\sigma_j}{\sigma_i}\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}\right),$$
$$k_{ij}=\frac{1}{1-\rho^2}\left(\frac{\theta(\mu_j-r^m)}{\alpha\sigma_j^2}-\rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i-r^m)}{\alpha\sigma_i^2}\right).$$

In a similar fashion, we obtain by an application of a symmetry argument for the lending decisions of bankers located in country j

$$k_{jj} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2} - \rho\frac{\sigma_i}{\sigma_j}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2}\right),$$
$$k_{ji} = \frac{1}{1-\rho^2}\left(\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2} - \rho\frac{\sigma_j}{\sigma_i}\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2}\right),$$

As a consequence, portfolio decisions are purely driven by stochastic processes of fundamental technology shocks. In this case, home bias is in turn given by

$$\mathcal{HB}_i = 1 - \frac{1+\frac{w_j}{w_i}}{2}\ .$$

As a result, home bias is solely driven by the ratio of loanable wealth, i.e., it decreases strictly in $\frac{w_j}{w_i}$. Home bias is thus independent of variations in monetary policy. Under Assumption 3, it is evident that home bias will equal throughout zero. This completes the proof of the second statement of Corollary 5.

□

Proof: Proposition

Proof Proposition 1.

Let us define the auxiliary parameters (Φ, Θ) by

$$\Phi = 1 - \frac{1}{\sigma_i^2}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2}, \tag{2.7.31}$$

$$\Theta = \frac{\sigma_j^2}{\sigma_i^2}\frac{\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^m)\sigma_\epsilon^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2}\ . \tag{2.7.32}$$

The interior candidate portfolio allocation of banks located in country i is given for domestic lending by

$$k_{ii} = \Phi^{-1}\Bigg(\underbrace{\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2}}_{\text{① Baseline CARA Effect}} - \underbrace{\Theta\frac{\theta(\mu_j - r^m)}{\alpha\sigma_j^2}}_{\text{② CARA Diversification Effect}} \underbrace{+\frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\Theta\left[1 - \psi(1-\omega\delta)r^m w_i\right]}_{\text{③ Manageable Risk Amplifier}}\Bigg), \tag{2.7.33}$$

and for cross border lending by

$$k_{ij} = \Phi^{-1}\Bigg(\underbrace{\frac{\theta(\mu_j - r^m)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2\right)}}_{④\text{ End. RA CARA}} - \underbrace{\Theta\frac{\sigma_i^2}{\sigma_j^2}\frac{\theta(\mu_i - r^m)}{\alpha\sigma_i^2}}_{⑤\text{ CARA Diversification Effect}} - \underbrace{\frac{1}{2}\zeta_i\sigma_\epsilon^2\frac{1-\psi(1-\omega\delta)r^f w_i}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^m)\sigma_\epsilon^2}}_{⑥\text{ Manageable Risk Effect}}\Bigg) . \tag{2.7.34}$$

The proof of Proposition 1 proceeds in three steps. In the first step, we derive the interior critical point $k^* = (k_{ii}^*, k_{ij}^*)$. In the second step, we derive a condition which ensures that k^* is a local maximum. We finally verify that the former condition also implies that k^* is the unique global solution to problem (P1′).

Proof. Part I: Derivation of Critical Point

The first order condition of bankers' portfolio choice problem from Lemma **??** are given by equations (2.7.21) and (2.7.22):

$$k_{ii} = \frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{k_{ij}}{\sigma_i^2}\left[\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right] ,$$

$$k_{ij} = \frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - k_{ii}\frac{\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} - \frac{\zeta_i}{2}\frac{\sigma_\epsilon^2\left(1-\psi(1-\omega\delta)r^f w_i\right)}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} .$$

Resubstitution of the second equation into the first one gives

$$k_{ii} = \frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{1}{\sigma_i^2}\left(\rho\sigma_i\sigma_j - \tfrac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\left(\frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - k_{ii}\frac{\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} - \frac{\zeta_i}{2}\frac{\sigma_\epsilon^2\left(1-\psi(1-\omega\delta)r^f w_i\right)}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\right)$$

Before we proceed, we define the following two auxiliary parameters:

$$\Phi \equiv 1 - \frac{1}{\sigma_i^2}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} , \quad \Theta \equiv \frac{\sigma_j^2}{\sigma_i^2}\frac{\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} .$$

Rearranging the above equation on domestic investment k_{ij} hence delivers

$$\Phi k_{ii} = \frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \Theta\frac{\theta(\mu_j - r^f)}{\alpha\sigma_j^2} + \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\Theta\left[1 - \psi(1-\omega\delta)r^f w_i\right] ,$$

which is equivalent to writing

$$k_{ii}^* = \Phi^{-1}\left(\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \Theta\frac{\theta(\mu_j - r^f)}{\alpha\sigma_j^2} + \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\Theta\left[1 - \psi(1-\omega\delta)r^f w_i\right]\right) . \tag{2.7.35}$$

To derive the cross border investment level k_{ij}, we resubstitute equation (2.7.35) into the corresponding first order condition to obtain

$$\begin{aligned} k_{ij} =& \frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - \frac{\zeta_i}{2}\frac{\sigma_\epsilon^2\left(1-\psi(1-\omega\delta)r^f w_i\right)}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} - \frac{\sigma_i^2}{\sigma_j^2}\Theta k_{ii} \\ =& \frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - \frac{\zeta_i}{2}\frac{\sigma_\epsilon^2\left(1-\psi(1-\omega\delta)r^f w_i\right)}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} \\ & - \frac{\sigma_i^2}{\sigma_j^2}\Theta\Phi^{-1}\left(\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \Theta\frac{\theta(\mu_j - r^f)}{\alpha\sigma_j^2} + \frac{1}{2}\frac{\zeta_i\sigma_\epsilon^2}{\sigma_j^2}\Theta\left[1-\psi(1-\omega\delta)r^f w_i\right]\right). \end{aligned}$$

The previous equation simplifies to

$$\begin{aligned} k_{ij} =& \frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)}\left(1 + \Phi^{-1}\frac{\sigma_i^2}{\sigma_j^4}\frac{\sigma_j^4}{\sigma_i^4}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\right) \\ & - \frac{1}{2}\zeta_i\sigma_\epsilon^2\frac{\left[1-\psi(1-\omega\delta)r^f w_i\right]}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\left(1 + \Phi^{-1}\frac{\sigma_i^2}{\sigma_j^4}\frac{\sigma_j^4}{\sigma_i^4}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\right) \\ & - \Phi^{-1}\Theta\frac{\sigma_i^2}{\sigma_j^2}\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2}. \end{aligned}$$

Further simplifications yield

$$1 + \Phi^{-1}\frac{\sigma_i^2}{\sigma_j^4}\frac{\sigma_j^4}{\sigma_i^4}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2} = \Phi^{-1}\left(\Phi + \frac{1}{\sigma_i^2}\frac{\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\right) = \Phi^{-1}.$$

As a result, we obtain

$$k_{ij}^* = \Phi^{-1}\left(\frac{\theta(\mu_j - r^f)}{\alpha\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)} - \Theta\frac{\sigma_i^2}{\sigma_j^2}\frac{\theta(\mu_i - r^f)}{\alpha\sigma_i^2} - \frac{1}{2}\zeta_i\sigma_\epsilon^2\frac{1-\psi(1-\omega\delta)r^f w_i}{\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2}\right), \tag{2.7.36}$$

which completes the first part of proof of Proposition 1.

Part II: Critical Point as Global Maximum

The objective function of bankers is defined as

$$\mathcal{U}(k_{ii}, k_{ij}) \equiv \mathbb{E}\left[u(e_i')|\mathcal{I}\right] = -\frac{1}{\alpha}e^{-\alpha\left(\mu_{e_i'} - \frac{1}{2}\alpha\sigma_{e_i'}^2\right)}. \tag{2.7.37}$$

k^* is a *strict local maximum* of $\mathcal{U}$ if the Hessian $\mathcal{H} \equiv D^2\mathcal{U}(k)$ is a negative definite symmetric matrix at $k = k^*$. This condition applies if and only if the two leading principal minors of $\mathcal{H}$ alternate in sign as follows: $|\mathcal{H}_1| < 0$ and $|\mathcal{H}_2| > 0$. The symmetric Hessian to (2.7.37) is denoted by

$$\mathcal{H} \equiv \begin{pmatrix} \mathcal{U}_{11} & \mathcal{U}_{12} \\ \mathcal{U}_{21} & \mathcal{U}_{22} \end{pmatrix} .$$

Moreover, let us define the following auxiliary parameters

$$\begin{aligned}
\Omega_{k_{ii}} &= -\alpha\theta(\mu_i - r^f) + \frac{1}{2}\alpha^2 \left[2\sigma_i^2 k_{ii} - \zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2 k_{ij} + 2\rho\sigma_i\sigma_j k_{ij}\right] , \\
\Omega_{k_{ij}} &= -\alpha\theta(\mu_j - r^f) + \frac{1}{2}\alpha^2 \left[2\sigma_j^2 k_{ij} - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 k_{ij} + \zeta_i\left(1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i{}'|\mathcal{I}\right]\right)\sigma_\epsilon^2 + 2\rho\sigma_i\sigma_j k_{ii}\right] .
\end{aligned}$$

The elements of the Hessian are then given by

$$\begin{aligned}
\mathcal{U}_{11} &= -\frac{1}{\alpha} e^{-\alpha(\mu_{e_i'} - \frac{1}{2}\alpha\sigma^2_{e_i'})} \left[\Omega^2_{k_{ii}} + \alpha^2\sigma_i^2\right] , \\
\mathcal{U}_{22} &= -\frac{1}{\alpha} e^{-\alpha(\mu_{e_i'} - \frac{1}{2}\alpha\sigma^2_{e_i'})} \left[\Omega^2_{k_{ij}} + \alpha^2\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)\right] , \\
\mathcal{U}_{12} &= -\frac{1}{\alpha} e^{-\alpha(\mu_{e_i'} - \frac{1}{2}\alpha\sigma^2_{e_i'})} \left[\Omega_{k_{ii}}\Omega_{k_{ij}} + \alpha^2\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\right] .
\end{aligned}$$

It is obvious that $|\mathcal{H}_1| < 0$ and $|\mathcal{H}_2| > 0$ are satisfied if $\mathcal{U}_{11} < 0$, $\mathcal{U}_{22} < 0$ and $\mathcal{U}_{11}\mathcal{U}_{22} - \mathcal{U}_{12}^2 > 0$. The first condition obviously holds without further restrictions. The second condition is satisfied if $\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2 > 0$. The third condition holds if

$$\sigma_i^2\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right) > \left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2 ,$$

which is equivalent to imposing $\Phi > 0$. Notice that in case the above inequality held with equality, the solution k^* would no longer be interior and finite, but rather located at the boundary.

To establish that k^* is a *global maximum*, we need to verify that $\mathcal{U}$ is a concave function on its entire convex domain $\mathbb{K}$, which is an open subset of $\mathbb{R}^2$. This is indeed the case if the Hessian $\mathcal{H}$ is negative semidefinite for all $k \in \mathbb{K}$. Notice that a local maximum requires a negative definite Hessian at a single interior point, whereas a global maximum requires that $\mathcal{H}$ is negative semidefinite not just at k^*, but for all $k \in \mathbb{K}$. The Hessian is negative semidefinite if every principal minor of odd order is weakly negative, and every principal minor of even order is weakly positive.

The two first order principal minors $\mathcal{U}_{11}$ and $\mathcal{U}_{22}$ are weakly negative by the above conditions. The second order principal component is weakly positive if

$$\left[\Omega_{k_{ii}}^2 + \alpha^2\sigma_i^2\right]\left[\Omega_{k_{ij}}^2 + \alpha^2\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)\right] \geq \left[\Omega_{k_{ii}}\Omega_{k_{ij}} + \alpha^2\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\right]^2 ,$$

which can be rewritten as

$$\alpha^2\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right)\Omega_{k_{ii}}^2 + \alpha^2\sigma_i^2\Omega_{k_{ij}}^2 + \alpha^4\sigma_i^2\left(\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2\right) \geq$$
$$2\alpha^2\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\Omega_{k_{ii}}\Omega_{k_{ij}} + \alpha^4\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2 .$$

The left hand side of the above inequality is strictly increasing in $\sigma_j^2 - \zeta_i\psi\theta(\mu_j - r^f)\sigma_\epsilon^2$. Substituting in its lower bound from the condition $\Phi > 0$ gives

$$\alpha^2\frac{1}{\sigma_i^2}\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)^2\Omega_{k_{ii}}^2 + \alpha^2\sigma_i^2\Omega_{k_{ij}}^2 - 2\alpha^2\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\Omega_{k_{ii}}\Omega_{k_{ij}} \geq 0 ,$$

which can be rewritten as

$$\alpha^2\left[\frac{1}{\sigma_i}\left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta_i\psi\theta(\mu_i - r^f)\sigma_\epsilon^2\right)\Omega_{k_{ii}} - \sigma_i\Omega_{k_{ij}}\right]^2 \geq 0 .$$

Due to the quadratic form, the above inequality is obviously satisfied for all $k \in \mathbb{K}$, such that k^* characterizes indeed an interior global maximum. This concludes the proof of Proposition 1. □

Proof Proposition 2.

Proof. Under Assumptions 2 and 3, the model-based home bias measure is given by

$$\mathcal{HB}_i = 1 - \frac{2}{1 + \frac{k_{ii}}{k_{ij}}} .$$

Its comparative statics in response to a change in monetary policy are thus captured by the ratio $\frac{k_{ii}}{k_{ij}}$. Based on Proposition 1 it can be written as

$$\frac{k_{ii}}{k_{ij}} = \frac{k_{jj}}{k_{ji}} = \frac{\frac{\theta(\mu-r^m)}{\alpha\sigma^2} - \Theta\frac{\theta(\mu-r^m)}{\alpha\sigma^2} + \frac{1}{2}\frac{\zeta\sigma_\epsilon^2}{\sigma^2}\Theta\left[1-\psi(1-\omega\delta)r^m w\right]}{\frac{\theta(\mu-r^m)}{\alpha(\sigma^2-\zeta\psi\theta(\mu-r^m)\sigma_\epsilon^2)} - \Theta\frac{\theta(\mu-r^m)}{\alpha\sigma^2} - \frac{1}{2}\zeta\sigma_\epsilon^2\frac{1-\psi(1-\omega\delta)r^f w}{\sigma^2-\zeta\psi\theta(\mu-r^m)\sigma_\epsilon^2}} \,.$$

Let us define auxiliary functions $(\mathcal{G}, \mathcal{F})$ as positively scaled functions of (k_{ii}, k_{ij}), i.e. such that $\frac{k_{ii}}{k_{ij}} = \frac{\mathcal{G}}{\mathcal{F}}$ applies, by

$$\mathcal{G} \equiv \sigma^2\left(\sigma^2 - \zeta\psi\theta(\mu-r^m)\sigma_\epsilon^2\right)k_{ii}$$
$$\mathcal{F} \equiv \sigma^2\left(\sigma^2 - \zeta\psi\theta(\mu-r^m)\sigma_\epsilon^2\right)k_{ij}$$

where it holds that

$$\mathcal{G} = \frac{\theta(\mu-r^m)}{\alpha}\left((1-\rho)\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu-r^m)\sigma_\epsilon^2\right) + \frac{1}{2}\zeta\sigma_\epsilon^2\left(\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu-r^f)\sigma_\epsilon^2\right)\left[1-\psi(1-\omega\delta)r^f w\right] \,,$$
$$\mathcal{F} = \frac{\theta(\mu-r^m)}{\alpha}\left((1-\rho)\sigma^2 + \frac{1}{2}\zeta\psi\theta(\mu-r^f)\sigma_\epsilon^2\right) - \frac{1}{2}\zeta\sigma_\epsilon^2\sigma^2\left[1-\psi(1-\omega\delta)r^f w\right] \,.$$

Based on the auxiliary functions, it is straightforward to derive

$$\begin{aligned}\frac{\partial\mathcal{F}}{\partial r^f} &= -\frac{\theta}{\alpha}(1-\rho)\sigma^2 - \frac{\theta}{\alpha}\frac{1}{2}\zeta\psi\theta(\mu-r^f)\sigma_\epsilon^2 - \frac{1}{2}\zeta\psi\theta\sigma_\epsilon^2\frac{\theta(\mu-r^m)}{\alpha} + \frac{1}{2}\zeta\sigma_\epsilon^2\sigma^2\psi(1-\omega\delta)w \\ &= -\frac{\theta}{\alpha}(1-\rho)\sigma^2 - \zeta\psi\theta\sigma_\epsilon^2\frac{\theta(\mu-r^m)}{\alpha} + \frac{1}{2}\zeta\sigma_\epsilon^2\sigma^2\psi(1-\omega\delta)w \,.\end{aligned}$$

In a similar vein, we obtain

$$\begin{aligned}\frac{\partial\mathcal{G}}{\partial r^f} =& -\frac{\theta}{\alpha}(1-\rho)\sigma^2 + \zeta\psi\sigma_\epsilon^2\frac{\theta^2(\mu-r^m)}{\alpha} + \frac{1}{4}\zeta^2(\sigma_\epsilon^2)^2\psi\theta\left[1-\psi(1-\omega\delta)r^f w\right] \\ & - \frac{1}{2}\zeta\sigma_\epsilon^2\left(\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu-r^f)\sigma_\epsilon^2\right)\psi(1-\omega\delta)w \\ =& -\frac{\theta}{\alpha}(1-\rho)\sigma^2 + \zeta\psi\sigma_\epsilon^2\frac{\theta^2(\mu-r^m)}{\alpha} + \frac{1}{4}\zeta^2\psi\theta(\sigma_\epsilon^2)^2 - \frac{1}{2}\zeta\sigma_\epsilon^2\psi(1-\omega\delta)w\left(\rho\sigma^2 - \frac{1}{2}\zeta\psi\theta(\mu-2r^f)\sigma_\epsilon^2\right) \,.\end{aligned}$$

It is straightforward to see that home bias increases in response to a monetary policy tightening if $\frac{\mathcal{G}}{\mathcal{F}}$ increases in r^f, i.e. if the following inequality holds

$$\frac{\partial\mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial\mathcal{F}}{\partial r^f}\mathcal{G} \geq 0 \,.$$

Part I: Proof Statement (a)

To show statement (a) of Proposition 2, notice that under $\omega = \delta^{-1}$, it follows that

$$\frac{\partial \mathcal{F}}{\partial r^f} < 0\,, \quad \text{and} \quad \frac{\partial \mathcal{F}}{\partial r^f} < \frac{\partial \mathcal{G}}{\partial r^f}\,.$$

Under Lemma 4, we also have $\mathcal{G} \geq \mathcal{F} \geq 0$. As a result, we obtain

$$\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} \geq \frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{F} = \left(\frac{\partial \mathcal{G}}{\partial r^f} - \frac{\partial \mathcal{F}}{\partial r^f}\right)\mathcal{F} \geq 0\,,$$

which concludes the proof of the first statement.

Part II: Proof Statement (b)

$\mathcal{A}$. *Idea of Proof.* The proof of statement (b) proceeds as follows. Whether bank home bias increases or decreases in response to a monetary policy tightening depends on the sign of the following equation

$$\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G}\,. \tag{2.7.38}$$

If the sign is positive, a monetary policy tightening increases home bias as in statement (a). If the sign is however negative, a monetary policy tightening decreases home bias respectively. From the initial derivations, we know the analytical counterparts to $\frac{\partial \mathcal{G}}{\partial r^f}$ and $\frac{\partial \mathcal{F}}{\partial r^f}$. Both derivatives are linear and continuously differentiable functions in *adjusted loanable wealth* $\tilde{w} \equiv (1 - \omega\delta)w$.

In the case of $0 \leq \omega < \delta^{-1}$, one can verify that $\frac{\partial \mathcal{F}}{\partial r^f}$ is strictly increasing in $\tilde{w}$, whereas the sign of $\frac{\partial \mathcal{G}}{\partial r^f}$ in $\tilde{w}$ is *a priori* ambiguous. Imposing Lemma 4, we also know that $\mathcal{G} \geq \mathcal{F}$ on the entire support of $\tilde{w}$. In the left limit $\tilde{w} = 0$, it thus follows by an equivalent argument as in the proof os statement (a) that $\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} \geq 0$. If additionally $\frac{\partial^2 \mathcal{F}}{\partial r^f \partial \tilde{w}} > \frac{\partial^2 \mathcal{G}}{\partial r^f \partial \tilde{w}}$ holds, it is possible to show that there exists a unique $\tilde{w}^*$ such that we obtain $\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} \geq 0$ for all $\tilde{w} \leq \tilde{w}^*$, respectively $\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} < 0$ for all $\tilde{w} > \tilde{w}^*$.

$\mathcal{B}$. *Characterization of parameter bounds for* (ψ, ρ).

Case 1: $\frac{\partial^2 \mathcal{F}}{\partial r^f \partial \tilde{w}} \geq \frac{\partial^2 \mathcal{G}}{\partial r^f \partial \tilde{w}}$. Case 1 applies if the following inequality holds

$$\rho - \frac{1}{2}\zeta\psi\theta(\mu - 2r^f)\frac{\sigma_\epsilon^2}{\sigma^2} > -1\,. \tag{2.7.39}$$

It is straightforward to see that this condition is always satisfied if $2r^f \geq \mu$. If on the contrary

$2r^f < \mu$ applies, case 1 holds if

$$\psi < \frac{2\sigma^2(1+\rho)}{\zeta\theta(\mu - 2r^f)\sigma_\epsilon^2} \equiv \overline{\psi}^{CT} . \tag{2.7.40}$$

A tighter sub-case of case 1 is given by imposing $\frac{\partial^2 \mathcal{G}}{\partial r^f \partial \tilde{w}} < 0$. This case indeed holds if

$$\rho \geq \frac{1}{2}\zeta\psi\theta(\mu - 2r^f)\frac{\sigma_\epsilon^2}{\sigma^2} \equiv \underline{\rho}$$

To be consistent with the upper bound $\overline{\rho}$ imposed in Lemma 4, one needs to verify that the following inequality holds

$$-1 < \frac{1}{2}\zeta\psi\theta(\mu - 2r^f)\frac{\sigma_\epsilon^2}{\sigma^2} < 1 - \frac{1}{2}\frac{\alpha\zeta\sigma_\epsilon^2}{\theta(\mu - r^f)} .$$

If $\overline{\rho} > 0$, the second inequality is obviously satisfied if $\mu \leq 2r^f$. In case that $\mu > 2r^f$ applies, we obtain an additional correlation driven upper bound on ψ, i.e.

$$\psi < \frac{2\sigma^2}{\zeta\theta(\mu - 2r^f)\sigma_\epsilon^2}\overline{\rho} \equiv \overline{\psi}^{CT} .$$

$\mathcal{C}$. Sufficient condition for $\mathcal{G} \geq \mathcal{F} \geq 0$ on entire support of $\tilde{w}$.

To begin with, let us define the support of the auxiliary variable $\tilde{w} \in \tilde{W} = [0, \overline{\tilde{w}}]$, where the upper bound $\overline{\tilde{w}}$ of the support is specified below. Additionally, let us denote by $\overline{\psi}^{\tilde{w}}$ the infimum of ψ over the set $\tilde{W}$ from Lemma 4, i.e.

$$\overline{\psi}^{\tilde{w}} \equiv \inf_{\tilde{w}\in[0,\overline{\tilde{w}}]} \overline{\psi}(\tilde{w}) = \inf_{\tilde{w}\in[0,\overline{\tilde{w}}]} \min\{\overline{\psi}^{GM,s}(\tilde{w}), \overline{\psi}_1^{(a),s}(\tilde{w}), \overline{\psi}^{(b),s}(\tilde{w})\} .$$

If $0 < \rho \leq \overline{\rho}$ and $\psi < \min\{\overline{\psi}^{CT}, \overline{\psi}^{\tilde{w}}\}$ applies, then $\frac{\partial \mathcal{F}}{\partial r^f}$ is strictly increasing in $\tilde{w}$, whereas $\frac{\partial \mathcal{G}}{\partial r^f}$ increases at most at a lower rate than $\frac{\partial \mathcal{F}}{\partial r^f}$ in $\tilde{w}$. As we have that $\frac{\partial \mathcal{F}}{\partial r^f} < \frac{\partial \mathcal{G}}{\partial r^f}$ at the left limit $\tilde{w} = 0$ and $\frac{\partial^2 \mathcal{F}}{\partial r^f \partial \tilde{w}} > \frac{\partial^2 \mathcal{G}}{\partial r^f \partial \tilde{w}}$ for all $\tilde{w} \in \tilde{W}$, we know that there exists a unique intersection point between both derivatives, which we subsequently denote by $\tilde{w}^{IS}$. Additionally, let us define the point at which $\frac{\partial \mathcal{F}}{\partial r^f}$ equals zero by $\tilde{w}^{\mathcal{F},0}$. It is given by

$$\tilde{w}^{\mathcal{F},0} = \frac{2}{\zeta\psi\sigma_\epsilon^2\sigma^2}\left(\frac{\theta}{\alpha}(1-\rho)\sigma^2 + \zeta\psi\sigma_\epsilon^2\frac{\theta^2(\mu - r^f)}{\alpha}\right) .$$

If $\tilde{w} \leq \tilde{w}^{\mathcal{F},0}$ applies, then $\frac{\partial \mathcal{F}}{\partial r^f} \leq 0$ holds and vice versa. Based on the previous notation, it is possible to derive a lower bound $\underline{\tilde{w}}$ such that it holds that

$$\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} \geq 0\,. \tag{2.7.41}$$

The lower bound depends on the fact whether the derivatives $(\frac{\partial \mathcal{G}}{\partial r^f}, \frac{\partial \mathcal{F}}{\partial r^f})$ intersect in the positive or negative orthant of $\mathbb{R}^2$. By Lemma 4 we have that $\mathcal{G} \geq \mathcal{F} \geq 0$, which implies that

(i) If $\tilde{w}^{IS} \leq \tilde{w}^{\mathcal{F},0}$ holds, equation (2.7.41) is positive if $\tilde{w} \leq \tilde{w}^{IS}$, as $\frac{\partial \mathcal{F}}{\partial r^f} \leq \frac{\partial \mathcal{G}}{\partial r^f} \leq 0$.

(ii) If $\tilde{w}^{IS} > \tilde{w}^{\mathcal{F},0}$ holds, equation (2.7.41) is positive if $\tilde{w} \leq \tilde{w}^{\mathcal{F},0}$, as $\frac{\partial \mathcal{G}}{\partial r^f} \geq 0$ and $\frac{\partial \mathcal{F}}{\partial r^f} \leq 0$.

As a result, a sufficient lower bound is given by $\underline{\tilde{w}} = \min\{\tilde{w}^{IS}, \tilde{w}^{\mathcal{F},0}\}$. By an analogous reasoning, one can characterize an upper bound $\overline{\tilde{w}}$ such that the following inequality holds

$$\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} < 0\,. \tag{2.7.42}$$

To do so, let us consider the subsequent case distinction by using again $\mathcal{G} \geq \mathcal{F} \geq 0$ from Lemma 4:

(i) If $\tilde{w}^{IS} \leq \tilde{w}^{\mathcal{F},0}$ holds, equation (2.7.42) is negative if $\tilde{w} \geq \tilde{w}^{\mathcal{F},0}$, as $\frac{\partial \mathcal{F}}{\partial r^f} \geq 0 \geq \frac{\partial \mathcal{G}}{\partial r^f}$.

(ii) If $\tilde{w}^{IS} > \tilde{w}^{\mathcal{F},0}$ holds, equation (2.7.42) is negative if $\tilde{w} \geq \tilde{w}^{IS}$, as $\frac{\partial \mathcal{F}}{\partial r^f} \geq \frac{\partial \mathcal{G}}{\partial r^f} \geq 0$.

As a result, we obtain $\overline{\tilde{w}} = \max\{\tilde{w}^{IS}, \tilde{w}^{\mathcal{F},0}\}$.

$\mathcal{D}$. Existence of unique intersection $\tilde{w}^*$.

It is straightforward to see that $\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G}$ is a second order polynomial in $\tilde{w}$, which is additionally continuously differentiable. By the intermediate value theorem, we hence know that there exists an odd number of intersection points at at which it holds that

$$\frac{\partial \mathcal{G}}{\partial r^f}\mathcal{F} - \frac{\partial \mathcal{F}}{\partial r^f}\mathcal{G} = 0\,.$$

As the left hand side of the previous equation is quadratic in $\tilde{\omega}$, it can has at most two intersection points. As a result, there exists a unique intersection point $\tilde{w}^* \in [\underline{\tilde{w}}, \overline{\tilde{w}}]$. Consequently, bank home bias increases in response to a monetary policy tightening if $\tilde{w} < \tilde{w}^*$ and increases on the contrary if $\tilde{w} > \tilde{w}^*$. Given the definition of $\tilde{w}$, we can define the separating frontier

$$\omega = \frac{1}{\delta}\left(1 - \frac{\tilde{w}^*}{w}\right)\,. \tag{2.7.43}$$

If ω is larger than the right hand side of (2.7.43), home bias increases in response to a monetary policy tightening, whereas it decreases if ω is smaller than the right hand side of (2.7.43). This completes the proof of Proposition 2.

$\mathcal{E}$. Rule out remaining case $\frac{\partial^2 \mathcal{G}}{\partial r^f \partial \bar{w}} \geq \frac{\partial^2 \mathcal{F}}{\partial r^f \partial \bar{w}} > 0$.

Case 2: $\frac{\partial^2 \mathcal{G}}{\partial r^f \partial \bar{w}} \geq \frac{\partial^2 \mathcal{F}}{\partial r^f \partial \bar{w}} > 0$. In this case, the marginal effect of monetary policy on domestic lending, $\frac{\partial \mathcal{G}}{\partial r^f}$, moves faster than the marginal effect of monetary policy on foreign lending, $\frac{\partial \mathcal{F}}{\partial r^f}$, in response to a change in bankers' loanable wealth w. It is only possible if the following inequality holds

$$\rho - \frac{1}{2}\zeta\psi\theta(\mu - 2r^f)\frac{\sigma_\epsilon^2}{\sigma^2} \leq -1\,,$$

which never holds if $\mu \leq 2r^f$. On the contrary, if $\mu > 2r^f$, the previous equation can be rearranged to

$$\psi \geq 2\frac{(1+\rho)\sigma^2}{\zeta\theta(\mu - 2r^f)\sigma_\epsilon^2}\,.$$

However, note that from Lemma 4 we assume the following restriction to ensure a global maximum of the bankers' problem,

$$\psi < \overline{\psi}^{GM,s} = 2\frac{\sigma^2}{\zeta\theta(\mu - r^f)\sigma_\epsilon^2}\left(\sqrt{2(1-\rho)} - (1-\rho)\right).$$

Therefore, to verify that there exists a set of parameter values for ψ which satisfies the inequality and the Lemma 4 restriction, the following equation needs to hold

$$\begin{aligned} 2\frac{(1+\rho)\sigma^2}{\zeta\theta(\mu - 2r^f)\sigma_\epsilon^2} &\leq 2\frac{\sigma^2}{\zeta\theta(\mu - r^f)\sigma_\epsilon^2}\left(\sqrt{2(1-\rho)} - (1-\rho)\right). \\ \Leftrightarrow \frac{(1+\rho)}{(\mu - 2r^f)} &\leq \frac{\sqrt{2(1-\rho)} - (1-\rho)}{(\mu - r^f)}\,. \end{aligned} \tag{2.7.44}$$

We now show that this is impossible. Given that $\rho \in [-1, 1]$, for $\rho = -1$, the above inequality holds with equality. As ρ increases, the left hand side increases at a higher rate in ρ compared to the right hand side, as the subsequent strict inequality applies

$$\frac{1}{\mu - 2r^f} > \frac{1}{\mu - r^f} - \frac{1}{(\mu - r^f)\sqrt{2(1-\rho)}}\,,$$

if $r^m \geq 0$. As a result, equation (2.7.44) never holds on the entire support of the fundamental correlation ρ. Therefore, we conclude that Case 2 is not consistent with the model assumptions, which completes the proof of Proposition 2. □

Bank Home Bias Index

Construction of Theoretical Bank Home Bias Measure.

Our tractable setup already provides a rich enough structure which allows to define and investigate the determinants of bank home bias fluctuations.

(a) Suppose that risk free asset holdings are neutral, i.e. it is counted neither as an investment to country i or j. The home bias measure is then given by

$$\mathcal{HB}_i = 1 - \frac{\frac{k_{ij}}{w_i}}{\frac{k_{ij}+k_{jj}}{w_i+w_j}} = 1 - \frac{1+\frac{w_j}{w_i}}{1+\frac{k_{jj}}{k_{ij}}} .$$

(b) Suppose that risk free asset holdings are domestic investment from the perspective of both countries. The home bias measure is then given by

$$\mathcal{HB}_i^* = 1 - \frac{\frac{k_{ij}}{w_i}}{\frac{k_{ij}+k_{jj}+b_j}{w_i+w_j}} = 1 - \frac{1+\frac{w_j}{w_i}}{1+\frac{k_{jj}+b_j}{k_{ij}}} .$$

(c) Suppose that risk free asset holdings are domestic assets from the perspective of country i and foreign to j. The home bias measures are then given by

$$\mathcal{HB}_i^{**} = 1 - \frac{\frac{k_{ij}}{w_i}}{\frac{k_{ij}+k_{jj}}{w_i+w_j}} = 1 - \frac{1+\frac{w_j}{w_i}}{1+\frac{k_{jj}}{k_{ij}}} ,$$

$$\mathcal{HB}_j^{**} = 1 - \frac{\frac{k_{ji}+b_j}{w_j}}{\frac{k_{ii}+k_{ji}+b_j+b_i}{w_j+w_i}} = 1 - \frac{1+\frac{w_i}{w_j}}{1+\frac{k_{ii}+b_i}{k_{ji}+b_j}} .$$

(d) Finally, suppose the unrealistic scenario that risk free asset holdings are foreign assets from the perspective of both countries. The home bias measure is then given by

$$\mathcal{HB}_i^{***} = 1 - \frac{\frac{k_{ij}+b_i}{w_i}}{\frac{k_{jj}+k_{ij}+b_i+b_j}{w_i+w_j}} = 1 - \frac{1+\frac{w_j}{w_i}}{1+\frac{k_{jj}+b_j}{k_{ij}+b_i}} .$$

An alternative definition of home bias, $\mathcal{HB}_i^a$, is based on the excess domestic share. Given that the baseline measure is defined as

$$\mathcal{HB}_i = 1 - \text{foreign share/world foreign share} \ ,$$

we may define

$$\mathcal{HB}_i^a = \text{domestic share/world domestic share} - 1 \ .$$

If risk free asset holdings are classified as domestic assets from the perspective of each country as in Case (b), or classified as domestic assets to only one country as in Case (c), the relationship between both home bias measures is given by

$$\mathcal{HB}_i^a = \frac{\text{Total investment into country j}}{\text{Total investment into country i}} \times \mathcal{HB}_i \ .$$

This relationship holds approximately for Case (a) and Case (d), as long as the risk-free investment is relatively low.

2.7.2 Quantitative Model

Dynamic Bank Problem

Solution

Euler Equation When market is incomplete, as in our model, Euler equation can be solved using guess-and-verify approach. We guess the forms of the value and the policy function:

$$V_t(w_{i,t}) = u(J_{i,t}(w_{i,t})) = u(\gamma_t w_{i,t} + \eta_{i,t}) \ , \quad \pi_{i,t} = \hat{\gamma}_{i,t} w_{i,t} + \hat{\eta}_{i,t} \ ,$$

where $\gamma_t, \hat{\gamma}_{i,t} \in \mathbb{R}_+$ and $\eta_{i,t}, \hat{\eta}_{i,t} \in \mathbb{R}$ are non-random coefficients. Envelope theorem implies

$$\frac{dV_t(w_{i,t})}{dw_{i,t}} = \frac{\partial u(\pi_{i,t})}{\partial \pi_{i,t}} \quad \Rightarrow \quad u'(J_{it}(w_{i,t}))\gamma_t = u'(\pi_{i,t})$$

Under CARA utility, this is equivalent to

$$e^{-\alpha(\gamma_t w_{i,t} + \eta_t)}\gamma_t = e^{-\alpha \pi_{i,t}} \quad \Rightarrow \quad \pi_{i,t} = \gamma_t w_{i,t} + \eta_t - \frac{1}{\alpha}\ln \gamma_t \ .$$

As a result, $\hat{\gamma}_t = \gamma_t$, and $\hat{\eta}_t = \eta_t - \frac{1}{\alpha}\ln \gamma_t$.

In addition, we have

$$\mathbb{E}_t\left[\pi_{i,t+1}\right] = \mathbb{E}_t\left[\gamma_{t+1} w_{i,t+1} + \eta_{t+1} - \ln \gamma_{t+1}\right] , \quad \mathrm{Var}(\pi_{i,t+1}) = \gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1}) .$$

We can then rewrite the expectation of the value function as

$$\begin{aligned}
\mathbb{E}_t V_{t+1}(w_{i,t+1}) &= -\frac{1}{\alpha} e^{-\alpha(\gamma_{t+1}\mu_{w_{i,t+1}} + \eta_{t+1}) + \frac{1}{2}\alpha^2 \gamma_{t+1}^2 \sigma_{w_{i,t+1}}^2} \\
&= -\frac{1}{\alpha} e^{-\alpha(\gamma_{t+1}(\mu_{w_{i,t+1}} - \frac{1}{2}\alpha\gamma_{t+1}\sigma_{w_{i,t+1}}^2) + \eta_{t+1})} \\
&= V_{t+1}\left(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\alpha\gamma_{t+1}\sigma_{w_{i,t+1}}^2\right) \\
&= V_{t+1}\left(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1})\right) \\
&= u(J_{i,t+1}(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1}))) .
\end{aligned}$$

where $\Gamma_{t+1} = \alpha\gamma_{t+1}$ reflects the effective absolute risk aversion at period t with respect to the wealth in period $t+1$.

The Bellman equation becomes

$$V_t(w_{i,t}) \equiv \max_{\{\pi_{i,t}, k_{ii,t+1}, k_{ij,t+1}, b_{i,t}\}} u(\pi_{i,t}) + \beta u(J_{i,t+1}(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1}))).$$

Using the budget constraint to substitute out $b_{i,t}$ and taking first order condition w.r.t. $\pi_{i,t}$, we have

$$\begin{aligned}
u'(\pi_{i,t}) &= -\beta \frac{\partial u(J_{i,t+1}(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1})))}{\partial \mathbb{E}_t w_{i,t+1}} \frac{\partial \mathbb{E}_t w_{i,t+1}}{\partial \pi_{i,t}} \\
&= \beta R_t^f \gamma_{t+1} u'(J_{i,t+1}(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1}))) \\
&= \beta R_t^f \gamma_{t+1} u'(\gamma_{t+1}(\mathbb{E}_t w_{i,t+1} - \frac{1}{2}\Gamma_{t+1}\mathrm{Var}(w_{i,t+1})) + \eta_{t+1}) \\
&= \beta R_t^f u'((\mathbb{E}_t \gamma_{t+1} w_{i,t+1} + \eta_{t+1} - \ln \gamma_{t+1}) - \frac{\alpha}{2}\gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1})) \\
&= \beta R_t^f u'(\mathbb{E}_t\left[\pi_{i,t+1}\right]) u'(-\frac{\alpha}{2}\mathrm{Var}(\pi_{i,t+1})).
\end{aligned}$$

Taking the natural logarithm on both sides, we get

$$\begin{aligned}
-\alpha\pi_{i,t} &= \ln(\beta R_t^f) - \alpha\left(\mathbb{E}_t\left[\pi_{i,t+1}\right] - \frac{\alpha}{2}\mathrm{Var}(\pi_{i,t+1})\right) , \\
\mathbb{E}_t\left[\pi_{i,t+1}\right] - \pi_{i,t} &= \frac{1}{\alpha}\ln(\beta R_t^f) + \frac{\alpha}{2}\mathrm{Var}(\pi_{i,t+1}) .
\end{aligned}$$

Thus we have derived the standard Euler equation under incomplete market.

Equivalently, we can rewrite the Euler equation using $w_{i,t+1}$

$$\mathbb{E}_t \left[\gamma_{t+1} w_{i,t+1} + \eta_{t+1} - \frac{1}{\alpha} \ln \gamma_{t+1} \right] - \pi_{i,t} = \frac{1}{\alpha} \ln \left(\beta R_t^f \right) + \frac{\alpha}{2} \gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1}) \ .$$

Portfolio Solution We can rewrite the expected value function has the following form

$$\mathbb{E}_t V_{t+1}(w_{i,t+1}) = u(\gamma_{0,t+1} + \gamma_{1,t+1} \mathbb{E}_t w_{i,t+1} + \gamma_{2,t+1} \mathrm{Var}(w_{i,t+1}))\ .$$

Note that the expression collapses to the simplified model case if $\gamma_{0,t+1} = \eta_{t+1}$, $\gamma_{1,t+1} = \gamma_{t+1}$, and $\gamma_{2,t+1} = -\frac{\alpha}{2}\gamma_{t+1}^2$.

The Bellman equation becomes

$$V_t(w_{i,t}) \equiv \max_{\{\pi_{i,t}, k_{ii,t+1}, k_{ij,t+1}, b_{i,t}\}} u(\pi_{i,t}) + \beta u(\gamma_{0,t+1} + \gamma_{1,t+1} \mathbb{E}_t w_{i,t+1} + \gamma_{2,t+1} \mathrm{Var}(w_{i,t+1})).$$

Recall that

$$\begin{aligned}
w_{i,t+1} =& \Delta d_{t+1} + R^l_{ii,t+1} k_{ii,t+1} + R^l_{ij,t+1} k_{ij,t+1} + R_t^f b_{i,t}\ , \\
\mu_{w_{i,t+1}} =& \Delta d_{t+1} + \mu_{ii,t+1} k_{ii,t+1} + \mu_{ij,t+1} k_{ij,t+1} + R_t^f b_{i,t}\ , \\
\sigma^2_{w_{i,t+1}} =& \sigma_i^2 k_{ii,t+1}^2 + k_{ij,t+1}^2 \left(\sigma_j^2 + \zeta_i (1 - \psi \mathbb{E}\left[\Delta \tilde{e}_{i,t+1} | \mathcal{I}\right]) \frac{1}{k_{ij,t+1}} \sigma_\epsilon^2 \right) + 2 k_{ii,t+1} k_{ij,t+1} \rho \sigma_i \sigma_j\ .
\end{aligned}$$

Taking first order condition w.r.t. $b_{i,t}$, we have

$$\begin{aligned}
u'(\pi_{i,t}) &= -\beta \frac{\partial u(\gamma_{0,t+1} + \gamma_{1,t+1} \mathbb{E}_t w_{i,t+1} + \gamma_{2,t+1} \mathrm{Var}(w_{i,t+1}))}{\partial \mathbb{E}_t w_{i,t+1}} \frac{\partial \mathbb{E}_t w_{i,t+1}}{\partial b_{i,t}} \\
&= \beta R_t^f \gamma_{1,t+1} u'(\Omega_{t+1})\ .
\end{aligned}$$

where $\Omega_{t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} \mathbb{E}_t w_{i,t+1} + \gamma_{2,t+1} \mathrm{Var}(w_{i,t+1})$.

Recall that pledgeable bank profitability is given by

$$\begin{aligned}
\mathbb{E}\left[p(\Delta \tilde{e}_{i,t+1}) | \mathcal{I}\right] =& (1 - \omega \delta_t) r_t^f w_{i,t} \\
& + \kappa_d \theta (\mu_{i,t+1} - (1 + \frac{\tau}{\theta}) R_t^f) k_{ii,t+1} + \kappa_f \theta (\mu_{j,t+1} - (1 + \frac{\tau}{\theta}) R_t^f) k_{ij,t+1}
\end{aligned}$$

First order conditions w.r.t. $k_{ii,t+1}$ and $k_{ij,t+1}$ yield

$$\begin{aligned}
(1+\tau)u'(\pi_{i,t}) =&\beta\frac{\partial u(\Omega_{t+1})}{\partial \mathbb{E}_t w_{i,t+1}}\frac{\partial \mathbb{E}_t w_{i,t+1}}{\partial K_{ii,t+1}}+\beta\frac{\partial u(\Omega_{t+1})}{\partial \mathrm{Var}(w_{i,t+1})}\frac{\partial \mathrm{Var}(w_{i,t+1})}{\partial k_{ii,t+1}}\\
=&\beta u'(\Omega_{t+1})\gamma_{1,t+1}\mu_i\\
&+\beta u'(\Omega_{t+1})\gamma_{2,t+1}\left[\left(2\sigma_i^2 k_{ii,t+1}+2k_{ij,t+1}\rho\sigma_i\sigma_j\right)\right]\\
&-\beta u'(\Omega_{t+1})\gamma_{2,t+1}\psi\left[\zeta_i\sigma_\epsilon^2\kappa_d\theta(\mu_{i,t+1}-(1+\frac{\tau}{\theta})R_t^f)k_{ij,t+1}\right],
\end{aligned}$$

$$\begin{aligned}
(1+\tau)u'(\pi_{i,t}) =&\beta\frac{\partial u(\Omega_{t+1})}{\partial \mathbb{E}_t w_{i,t+1}}\frac{\partial \mathbb{E}_t w_{i,t+1}}{\partial K_{ij,t+1}}+\beta\frac{\partial u(\Omega_{t+1})}{\partial \mathrm{Var}(w_{i,t+1})}\frac{\partial \mathrm{Var}(w_{i,t+1})}{\partial k_{ij,t+1}}\\
=&\beta u'(\Omega_{t+1})\gamma_{1,t+1}\mu_j\\
&+\beta u'(\Omega_{t+1})\gamma_{2,t+1}\left[\left(2\sigma_j^2 k_{ij,t+1}+2k_{ii,t+1}\rho\sigma_i\sigma_j\right)\right]\\
&-\beta u'(\Omega_{t+1})\gamma_{2,t+1}\psi\left[\zeta_i\sigma_\epsilon^2\kappa_f\theta(\mu_{j,t+1}-(1+\frac{\tau}{\theta})R_t^f)k_{ij,t+1}\right]\\
&+\beta u'(\Omega_{t+1})\gamma_{2,t+1}\zeta_i\left(1-\psi\mathbb{E}\left[\Delta\tilde{e}_{i,t+1}|\mathcal{I}\right]\right)\sigma_\epsilon^2 .
\end{aligned}$$

We can see that if $\psi=0$, the solution collapses to that of the simplified model. Define the augmented parameters by

$$\begin{aligned}
\tilde{\sigma}_\epsilon^2 &= \sigma_\epsilon^2\left[1-\psi(1-\omega\delta)w_{i,t}(R_t^f-1)\right],\\
\tilde{\sigma}_j^2 &= \sigma_j^2-\kappa_f\zeta_i\psi\theta(\mu_{j,t+1}-(1+\frac{\tau}{\theta})R_t^f)\sigma_\epsilon^2,\\
\tilde{\rho} &= \frac{\left(\rho\sigma_i\sigma_j-\frac{\kappa_d}{2}\zeta_i\psi\theta(\mu_{i,t+1}-(1+\frac{\tau}{\theta})R_t^f)\sigma_\epsilon^2\right)}{\sigma_i\tilde{\sigma}_j}.
\end{aligned}$$

Solving the previous system of equations for $k_{ii,t+1}, k_{ij,t+1}$, we have

$$\begin{aligned}
k_{ii,t+1} &= \frac{1}{1-\tilde{\rho}^2}\left[\frac{\mu_i-(1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i^2}-\tilde{\rho}\frac{\mu_j-(1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i\tilde{\sigma}_j}+\frac{1}{2}\tilde{\rho}\frac{\zeta_i\tilde{\sigma}_\epsilon^2}{\sigma_i\tilde{\sigma}_j}\right],\\
k_{ij,t+1} &= \frac{1}{1-\tilde{\rho}^2}\left[\frac{\mu_j-(1+\tau)R_t^f}{\alpha\gamma_{t+1}\tilde{\sigma}_j^2}-\tilde{\rho}\frac{\mu_i-(1+\tau)R_t^f}{\alpha\gamma_{t+1}\sigma_i\tilde{\sigma}_j}-\frac{1}{2}\frac{\zeta_i\tilde{\sigma}_\epsilon^2}{\tilde{\sigma}_j^2}\right].
\end{aligned}$$

where $\gamma_{t+1}=-2\frac{\gamma_{2,t+1}}{\gamma_{1,t+1}}$.

Using the bank's budget constraint, we obtain the expression for the risk-free asset,

$$\begin{aligned} b_{i,t} &= w_{i,t} - \pi_{i,t} - (1+\tau)k_{ii,t+1} - (1+\tau)k_{ij,t+1} \\ &= (1-\gamma_t)w_{i,t} - \eta_t + \frac{1}{\alpha}\ln\gamma_t - (1+\tau)k_{ii,t+1} - (1+\tau)k_{ij,t+1} \,. \end{aligned}$$

Note that

$$\begin{aligned} w_{i,t+1} =& \Delta d_{t+1} + R^l_{ii,t+1}k_{ii,t+1} + R^l_{ij,t+1}k_{ij,t+1} + R^f_t\left(w_{i,t} - \pi_{i,t} - (1+\tau)(k_{ii,t+1} + k_{ii,t+1})\right) , \\ \mu_{w_{i,t+1}} =& \Delta d_{t+1} + \mu_{ii,t+1}k_{ii,t+1} + \mu_{ij,t+1}k_{ij,t+1} + R^f_t\left(w_{i,t} - \pi_{i,t} - (1+\tau)(k_{ii,t+1} + k_{ii,t+1})\right) \\ =& \Delta d_{t+1} + \mu_{ii,t+1}k_{ii,t+1} + \mu_{ij,t+1}k_{ij,t+1} \\ &+ R^f_t\left(w_{i,t} - (\gamma_t w_{i,t} + \eta_t - \ln\gamma_t) - (1+\tau)(k_{ii,t+1} + k_{ii,t+1})\right) . \end{aligned}$$

Variance of next period wealth is given by

$$\begin{aligned} \mathrm{Var}w' =& \sigma_i^2k_i^2 + \sigma_j^2k_j^2 + 2\rho\sigma_i\sigma_jk_ik_j + \zeta\big(1 - \psi\mathbb{E}\left[\Delta\tilde{e}_i\right]\big)k_j\sigma_\epsilon^2 \\ =& \sigma_i^2k_i^2 + \sigma_j^2k_j^2 + 2k_ik_j\rho\sigma_i\sigma_j + \zeta\sigma_\epsilon^2k_j \\ & - \zeta\psi(1-\omega\delta)wr^fk_j\sigma_\epsilon^2 + \zeta\psi\kappa_d\theta(\mu_i - r^f)k_ik_j\sigma_\epsilon^2 + \zeta\psi\kappa_f\theta(\mu_j - r^f)k_j^2\sigma_\epsilon^2 \\ =& \sigma_i^2k_i^2 + (\sigma_j^2 - \zeta\psi\kappa_f\theta(\mu_j - r^f)\sigma_\epsilon^2)k_j^2 + \left(\rho\sigma_i\sigma_j - \frac{1}{2}\zeta\psi\kappa_d\theta(\mu_i - r^f)\right)2k_ik_j \\ & + \zeta(1 - \psi(1-\omega\delta)wr^f)\sigma_\epsilon^2k_j \\ =& \sigma_i^2k_i^2 + \tilde{\sigma}_j^2k_j^2 + 2\tilde{\rho}\sigma_i\tilde{\sigma}_jk_ik_j + \zeta\tilde{\sigma}_\epsilon^2k_j \end{aligned}$$

We can see that wealth effect appears because of the pledgeability of risk-free profit, which is reflected by w showing up in $\tilde{\sigma}_\epsilon^2$. Generalized correlation depends on the pledgeability of domestic asset, which is reflected by $\tilde{\rho}$. Variance reduction depends on the pledgeability of foreign asset, which is reflected by $\tilde{\sigma}_j^2$.

Since wealth effect does not depends on $\tilde{\rho}$ and $\tilde{\sigma}_j^2$, we can shut down these two channels simply by imposing $\kappa_d = \kappa_f = 0$.

Undetermined Coefficients Finally, we have to determine the coefficients (γ_t, η_t). From Euler equation we have

$$\gamma_{t+1}\mu_{w_{i,t+1}} + \eta_{t+1} - \frac{1}{\alpha}\ln\gamma_{t+1} - \gamma_t w_{i,t} - \eta_t + \frac{1}{\alpha}\ln\gamma_t = \frac{1}{\alpha}\ln(\beta R_t^f) + \frac{\alpha}{2}\gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1})$$

$$\gamma_t w_{i,t} + \eta_t - \frac{1}{\alpha}\ln\gamma_t = \left(\gamma_{t+1}\mu_{w_{i,t+1}} + \eta_{t+1} - \frac{1}{\alpha}\ln\gamma_{t+1}\right) - \frac{1}{\alpha}\ln(\beta R_t^f) - \frac{\alpha}{2}\gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1})$$

$$\gamma_t w_{i,t} + \eta_t = \left(\gamma_{t+1}\mu_{w_{i,t+1}} + \eta_{t+1}\right) - \frac{1}{\alpha}\ln(\beta R_t^f \frac{\gamma_{t+1}}{\gamma_t}) - \frac{\alpha}{2}\gamma_{t+1}^2 \mathrm{Var}(w_{i,t+1})$$

$$\begin{aligned}\gamma_{t+1}\mu_{i,t+1} =& \gamma_{t+1}R_t^f w_{i,t}(1-\gamma_t) \\ &- \gamma_{t+1}R_t^f(1+\tau)\frac{1}{1-\tilde{\rho}^2}\frac{1}{2}\left(\frac{\tilde{\rho}\zeta_i}{\alpha\sigma_i\tilde{\sigma}_j} - \frac{\zeta_i}{\alpha\tilde{\sigma}_j^2}\right)\sigma_\epsilon^2\left[-\psi(1-\omega\delta)w_{i,t}(R_t^f-1)\right]\end{aligned}$$

$$\gamma_t = \gamma_{t+1}R_t^f\left[1-\gamma_t - \mathcal{A}(R_t^f-1)\right]$$

$$\frac{1}{\gamma_{t+1}} = \frac{R_t^f\left[1-\mathcal{A}(R_t^f-1)\right]}{\gamma_t} - R_t^f$$

Steady State The steady state values generated by the dynamic bank problem is given in Table 2.3.

Table 2.3: Steady State Values.

Parameter	Description	Value
e	Equity	2.60852
d	Deposit	6.08654
w	Total asset/liability	8.69506
k_i	Domestic lending	3.83177
k_j	Foreign lending	2.01349
L	Total loan	5.84526
HB	Home bias	0.474528
b	Risk-free asset	2.66993
π	Dividend	0.179871
$\mathrm{Var}(w)$	Portfolio variance	6.312
R_f	Risk-free rate	1.00828
R_d	Deposit rate	1.00289

Complete Model

Solution

Figure 2.16 shows the structure of the open economy in the quantitative model.

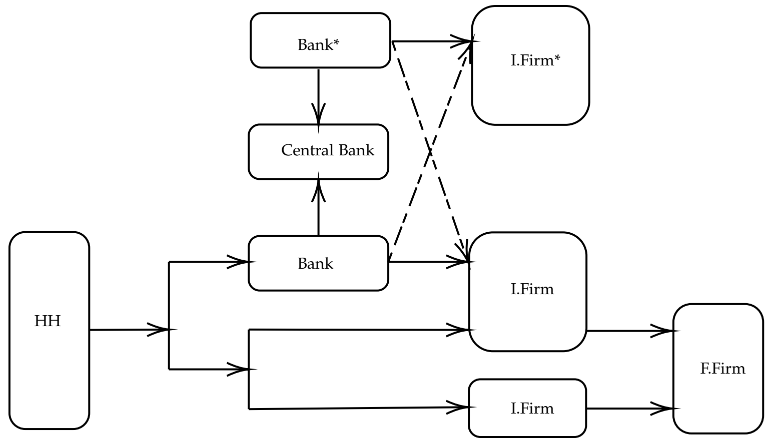

Figure 2.16: Structure of the Economy.

Household Without nominal rigidity, the households solve

$$\max_{C_t,N_t,D_t,K_{t+1}} \mathbb{E}\sum_{t=0}^{\infty}\beta^t\mathcal{U}(C_t,N_t)$$
$$\text{s.t.}\quad D_{t+1}+K_{t+1}\leq W_tN_t+R_t^kK_t+R_t^dD_t+\Pi_t$$
$$C_t\leq R_{t+1}^dD_{t+1}\theta_d$$

First order conditions with respect to C_t, N_t, D_{t+1}, and K_{t+1} yield

$$\begin{aligned}U'(C_t)=&C_t^{-\sigma}=Q_t\ ,\\U'(N_t)=&-\chi(1-N_t)^{-\varphi}=-\lambda_t^hW_t\ ,\\\lambda_t^h=&\beta\lambda_{t+1}^hR_{t+1}^k\ ,\\\lambda_t^h=&\beta\lambda_{t+1}^hR_{t+1}^d+Q_t\theta_dR_{t+1}^d\ ,\end{aligned}$$

where λ_t^h and Q_t are the Lagrangian multipliers for budget constraint and deposit constraints respectively.

Production firms Production firms solve the profit maximization problem. First-order conditions yield

$$\begin{aligned}0=&\alpha P_{I,t}\bar{A}K_t^{\alpha-1}N_t^{1-\alpha}-R_t^k-\lambda_t^fR_t^k\\0=&(1-\alpha)P_{I,t}\bar{A}K_t^{\alpha}N_t^{-\alpha}-W_t-\lambda_t^fW_t\\0=&(L_t-R_t^kK_t-W_tN_t)\lambda_t^f\end{aligned}$$

where λ_t^f is the Lagrangian multiplier for the expenditure constraint.

Final firms The first-order condition of the final retailers is given by

$$\left((1-\varepsilon)\left(\frac{P^*_{f,t}}{P_t}\right)^{1-\varepsilon} + \varepsilon P_{I,t}\left(\frac{P^*_{f,t}}{P_t}\right)^{-\varepsilon} - \phi\left(\frac{P^*_{f,t}}{P_{f,t-1}} - 1\right)\frac{P^*_{f,t}}{P_{f,t-1}}\right) Y_t$$
$$+\phi E_t \beta^j \Lambda_{t,t+1}\left(\frac{P^*_{f,t+1}}{P_{f,t}} - 1\right)\frac{P^*_{f,t+1}}{P_{f,t}} Y_{t+1} = 0 \, .$$

Monetary Policy Rule

$$\begin{aligned}
\pi_{t+1} - \pi_t &= 1/\alpha \ln(\beta R f_t) + \alpha/2(\gamma_t^2)\,\mathrm{Var}(w_t) \\
0 &= 1/\alpha \ln(\beta R^*) + \alpha/2(\gamma^2)\,\mathrm{Var}(w^*) \\
0 &= \ln(\beta R^*) + \alpha^2/2(\gamma^2)\,\mathrm{Var}(w^*) \\
ln(R^*) &= \ln\left(\frac{1}{\beta}\right) - \alpha^2/2(\gamma^2)\,\mathrm{Var}(w^*) \\
R^* &= \exp\left(\ln\left(\frac{1}{\beta}\right) - \frac{\alpha^2}{2}\gamma^2\,\mathrm{Var}(w^*)\right)
\end{aligned}$$

Parameter

Table 2.4: Parameters.

Parameter	Description	Value
β	discount factor	0.990
α	CARA risk-aversion	3.000
μ_i & μ_j	mean of return on domestic and foreign project	1.030
σ_i & σ_j	standard deviation of domestic and foreign project return	0.500
ρ	correlation between domestic and foreign project	-0.100
σ_ϵ	standard deviation of uncertainty	2.5 $\times\sigma_i$
ω	pass-through elasticity from risk-free rate to deposit rate	0.750
δ	deposit to asset ratio	0.800
ζ	Overall management efficiency	0.950
ψ	Management cost reduction w.r.t wealth	6.000
κ_d	Pledgeability of domestic loan	0
κ_f	Pledgeability of foreign loan	0
τ	regulation cost on risky projects	0.000
θ	bargain parameter	1.000

Results

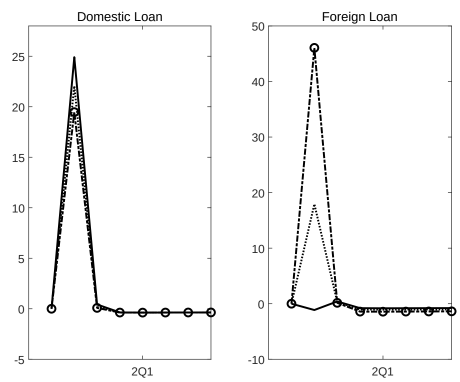

Figure 2.17: Responses of to Nominal Rate Cut.

Notes: The solid line, dash line, and dash line with circles are respectively the impulse responses of the model with ψ equal to 6, 4 and 2.

Chapter 3

Country-level Bank Home Bias: An Empirical Investigation

Li Yu and Philipp Wangner[1]

3.1 Introduction

Cross-border lending by international banks has been decreasing since the Great Recession. The ratio between outstanding international claims and world GDP goes down from over 60% to around 40% (McCauley et al., 2021). In European Union, cross-border claims by banks dropped by 25% (Emter et al., 2019). However, these figures do not provide a comprehensive picture of banks' lending preferences with regard to geographical location. It is possible that the decline in cross-border claims is not solely due to a reduction in foreign claims but rather a symmetric decrease in domestic and foreign claims. Using the share of foreign lending to total lending, as opposed to absolute levels, mitigates this issue. Nevertheless, this measure still fails to distinguish between the supply-side and demand-side factors that may be driving the decline in cross-border lending, i.e., whether the reduction is a result of decreased demand for credit abroad or a shift in banks' lending allocation.

Given the importance of cross-border intermediation in deepening financial integration across economies, understanding banks' true preference for cross-border lending is critical in designing and conducting effective monetary and macroprudential policies. More impor-

[1] We are extremely grateful to Patrick Fève, Fabrice Collard, Christian Hellwig, and Nicolas Werquin for their invaluable advice and continuous support. All remaining errors are our own.

tantly, recent studies have also highlighted potential threats to domestic financial stability due to the exposure to international regulatory coordination (Calzolari and Loranth, 2011), cross-border monetary policy transmission (Correa et al., 2018), or cross-border externalities faced by multinational banks (Clayton and Schaab, 2021). As such, the dual nature of cross-border credit flows calls for a closer examination of banks' lending preferences to ensure both the effectiveness of monetary policy and financial stability.

This paper investigates banks' cross-border lending preferences. We adopt a uniform measurement of relative bank lending preferences, the *bank home bias* index. This index is widely used in studies on cross-border equity investment and is first applied to bank lending by Coeurdacier and Rey (2013). It is constructed so that the cross-border asset share of a given investment portfolio is normalized by the corresponding share of the foreign asset in the world portfolio. By doing so, it distinguishes between the case of a cut in foreign lending due to the lack of investment opportunities abroad and a decrease in the preference for foreign assets. That is, a higher home bias index always indicates a lower preference for cross-border lending activities.[2] Given the definition of home bias, our paper provides novel empirical evidence on country-level bank home bias, examines the potential driving forces for home bias variations, and studies the implication of bank home bias variation for business cycle fluctuations.

To start with, we build the country-level home bias index for over thirty countries and measure bank home bias country-wise. To this end, we collect data on the domestic and cross-border lending of banks from over thirty countries and build country-wise bank home bias since the early 2000s at a quarterly frequency. The overall trend of bank home bias exhibits a V-shaped pattern. Before the crisis, the weighted average bank home bias steadily decreased. The downward trend ceased to continue after the Great Recession, as the home bias level bounced back by over 8% from the historical low and remained high even after the recession ended. The pattern conforms with the recent empirical documentation on the persistent low levels of foreign lending. Moreover, this V-shaped bank home bias is in stark contrast with equity home bias, which has steadily decreased during the same period. This departure suggests that promising determinants for explaining home bias fluctuations are either specific to the banking sector or affect bank and equity investors differently.

Based on the observations of home bias variations, we investigate the key driving factors of bank home bias variations, particularly the role of uncertainty and interest rates. Using the

[2] Essentially, this indicator can be understood as a measure of the degree of financial integration of the banking sector. A home bias of 1 indicates that the banking sector is in a state of autarky. In contrast, a home bias of 0 implies that the bank portfolio is fully diversified in domestic and foreign assets. For a more detailed explanation of the index construction, see Section 3.2.1 and Appendix 3.8.2.

Economic Policy Uncertainty Index (Baker et al., 2016) and the World Uncertainty Index (Ahir et al., 2018), we find that uncertainty exhibits a strikingly similar trend as bank home bias. Further structural analysis confirms that foreign uncertainty has a crucial impact on bank home bias variations. Using US data, we estimate structural vector auto-regression (SVAR) models, including macro variables and banking sector characteristics. The models suggest that uncertainty, particularly foreign uncertainty, is a substantial driver for bank home bias fluctuations. An increase in foreign uncertainty increases bank home bias significantly. The shock accounts for over half of the forecast error variances. For the effect of interest rate, our findings suggest that the Great Recession led to a structural break in the impact of the policy rate on the home bias. The prolonged period of the low-interest rate after the crisis negatively impacted bank home bias. The effect of a policy rate change can also be state-dependent, determined by the banking sector's profitability.

Lastly, we study the implication of bank home bias by examining its business cycle. By computing the correlation between the cyclical component of the bank home bias series and the corresponding GDP series, we find that domestic economic growth is associated with lower home bias prior to the Great Recession. However, the effects no longer exist after the crisis. The results suggest a structural break in the banking sector or the banks' lending patterns, of which one potential reason is the low-interest rate period after the recession.

Literature Our findings speak to the burgeoning literature on the documentation of the geographical allocation of investment. The index we use to capture lending preference, namely the home bias index, is commonly used in the analysis of equity and bond investment (Hau and Rey, 2008; Coeurdacier and Gourinchas, 2011, 2016). The index has been adapted to bank lending in recent research, as Coeurdacier and Rey (2013) empirically document bank home bias for different world regions. Our paper follows this empirical approach and provides more detailed documentation of bank home bias, with observations collected quarterly for over thirty countries over twenty years. To identify the causes of the bias, Mondria et al. (2010) use a search index to show that the extent of information acquisition for domestic and foreign investment differs. Using SVAR models, we confirm the role of informational friction by exhibiting the importance of second-order moments, or uncertainty (Bloom, 2009; Ahir et al., 2018; Baker et al., 2016; Berger et al., 2020), in driving bank home bias variations.

Layout The rest of the paper is structured as follows. Section 3.2 introduces the index of bank home bias and the construction using country-level data. Section 3.3 studies the key drives of bank home bias, namely monetary policy and uncertainty, taking the United States as an example. Section 3.4 extends the analysis to a panel of countries in our sample. Section 3.5 studies the cyclicality of bank home bias. Finally, Section 3.6 concludes.

3.2 Bank Home Bias Index

3.2.1 Index Construction

We start by introducing the measure we use to capture cross-border lending activities. We do not use the levels of cross-border claims as the measure, as this ratio alone cannot distinguish between a retreat from the foreign market and a symmetric reduction in domestic and foreign claims. Nor does it capture the demand-side effects, i.e. whether the reduction is due to low demand for credit abroad or a change in banks' lending preference. The home bias index improves on these issues since the index is defined in such a way that the cross-border asset share of a given investment portfolio is normalized by the corresponding share of the foreign asset in the world portfolio. With this normalization process, the index can distinguish between the case of a cut in foreign lending due to the lack of investment opportunities abroad and that of a pure decrease in preference. Therefore, bank home bias can be intuitively understood as a deviation from a *neutral* level of preference for foreign assets. The construction of this concept thus boils down to: (i) specifying a benchmark portfolio consisting of foreign and domestic asset holdings, and (ii) measuring how far the actual portfolio deviates from this benchmark level. In the context of international financial markets, we follow the practice of Coeurdacier and Rey (2013) and define the benchmark portfolio as a diversified portfolio in the CAPM sense. It implies that the share of foreign asset holdings in this portfolio (i.e. *portfolio foreign share*) equals the share of investment into foreign countries in the world's total investment (i.e. *world portfolio foreign share*).

Our computation of bank home bias is at the country level. The countries are indicated by $i \in I$. Denote by d_i the domestic asset holdings of country i's banks, and c_i the cross-border asset holdings. Suppose the home country is country i^*. To compute the benchmark portfolio for country i^*, we first need to compute the total investment to countries that are foreign to country i^*, which equals $\Sigma_{i \neq i^*} d_i + \Sigma_{i \neq i^*}(c_i - c_i^{i^*}) + c_{i^*}$. The first term denotes all the other countries' domestic investments. The second term is all the other countries' cross-border investment, net of the investment that goes to the country i^*. Finally, the third term is the cross-border investment of the home country i^*. The world's total investment is given by $\Sigma_{i \in I}(c_i + d_i)$. Based on this definition, the formula for bank home bias is given by:

$$\mathcal{HB}_{i^*} \equiv 1 - \frac{\text{portfolio foreign share of } i^*}{\text{world portfolio foreign share of } i^*} = 1 - \frac{\frac{c_{i^*}}{c_{i^*}+d_{i^*}}}{\frac{\Sigma_{i \neq i^*} d_i + \Sigma_{i \neq i^*}(c_i - c_i^{i^*}) + c_{i^*}}{\Sigma_i (c_i + d_i)}} . \qquad (3.2.1)$$

The index denotes a *real measure* which lies in the range $[0, 1]$[3], if all asset positions are weakly positive. For a given world foreign share, the upper bound of unity is reached if banks of country i do not engage in cross-border lending. The index is zero if the banks of country i have a portfolio foreign share equal to the world foreign share.

3.2.2 Data and Variable

This section documents the construction of the bank home bias index, including data sources, data processing, and variable definitions.

Construction of Domestic Lending. For domestic lending, we use the variables from IMF International Financial Statistics (IFS) dataset. The entity that classify as bank in this data set is *Other Depository Corporations*, and according to the newest (as of January 2020) *International Financial Statistics: Introductory Notes*, the domestic assets consists of three components: *Claims on Central Bank*, *Claims on Central Government*, and *Claim on Other Sector*. These three variables are available for most countries. After obtaining these variables, we convert the value to US dollar in order to have a consistent comparison across countries.

Construction of Foreign Lending. For foreign lending data, we turn to the Locational Banking Statistics (LBS) dataset from Bank for International Settlements. Two issues to be resolved when using LBS dataset is first, defining the nationality of banks and second, classifying what counts as foreign lending. In LBS, one can specify the parent country, the reporting country, and the counterpart country. This gives rises to two possibility of identifying a country's banking sector: the bank that is owned by the shareholder of the nationality, and the banks that currently resides in side the country. In practice, we go for the second definition. This is because once one specify the parent country, the recipient country is only available as a total

[3]Note that the definition of home bias index allows for a range of $(-\infty, 1]$. It becomes negative if relative cross-border lending is above the world's foreign share. This is, however, rarely the case in our dataset. With the exception of a few countries, the domestic investment share is always larger. Therefore, we restrict our analysis to the case where home bias is larger than zero.

sum instead of in country-wise form. Therefore, our classification of bank is location-oriented, instead of nationality-oriented.

In terms of the definition of foreign lending, we cite the newest (as of July 2019) *Reporting guidelines for the BIS international banking statistics*. According to this report, *cross-border lending* includes the lending activities in which the two parties involved resides in different countries, as opposed to *local lending*, in which borrower and lender are in the same country. *Foreign lending* and *Domestic Lending*, on the other hand, are defined in a different manner. Foreign lending refers to the lending in which the recipient is different from the nationality of the lending bank. Consequently, cross-border lending and foreign lending overlaps to a large degree, but there are certain differences when it comes to banks foreign branches.

In our research, the lending behavior we seek to capture is closer to the definition of foreign lending. However, as stated previously, we are only able to define banks based on location instead of nationality, due to data limitation. Thus we proceed to define our **foreign lending** as the *cross-border lending conducted by these banks resides in that country*.

This is obviously only a proxy to the true foreign lending. Nevertheless, we think the difference will not sabotage our main conclusions. Comparing to the foreign lending definition of BIS, our measure misclassify the lending to foreign countries done by a foreign branch as domestic, and the lending to home countries by foreign branch as foreign. To put things into perspective, if the French Bank BNP Paribas has a foreign branch in Germany, our measure would classify its lending to Mercedes Benz as domestic, while its lending to Renault foreign. However, as long as these two cancels out to some extent, our measure would still be fairly close to the true foreign lending. Furthermore, since foreign branches usually consist of a fairly small share of the banking sector, the extent to which this proxy may affect our results is limited. Thus in this research, we use the word cross-border lending and foreign lending interchangeably.

Construction. After obtaining domestic and foreign lending data from IFS and LBS, we merge them to form a dataset with complete bank portfolios. The merged final dataset contains 32 countries, which covers major developed countries and several developing countries. Recall the definition of home bias:

$$\text{Home Bias of Country } i = 1 - \frac{A_i}{B_i},$$

where

$$A_i = \frac{a_i^1}{a_i^2} == \frac{\text{Cross-border Claims of Country } i}{\text{Cross-border Claims of Country } i \text{ + Domestic Claims of Country } i},$$

and

$$B_i = \frac{b_i^1}{b_i^2} == \frac{\text{World Foreign Lending}_i}{\text{World Total Lending}}.$$

This measurement seeks to capture home bias as a deviation from a benchmark, measured as the ratio between the foreign share of a country's bank portfolio, A_i, and the foreign share of a benchmark world portfolio B_i respective to country i. For example, if United State banks investment 80% of their claims domestically ($A_{US} = 1 - 80\% = 20\%$), it does not necessarily reflect a high home bias: It might as well be the case that most of the world's investment opportunities occur in the US. It is the deviation that counts as bias. That's why we need a world benchmark to determine whether the bias exists.

Using this panel of countries as *world*, we compute the total amount of lending (both domestic and foreign) as *World Total Lending*. The question is then to determine what counts as *World Foreign Lending*. One might think that the most straightforward way to define it is to sum the foreign lending of each country and use it as the total amount of foreign lending in this world. However, we believe that this approach does not correctly achieve our goal. One reason is that this measure would be the same to all countries. More importantly, it measures *de facto* foreign lending, instead of what *de jure* foreign lending in an ideal world of full diversification, given each countries demand for credit.

For this reason, we adopt the following country-specific measurement for *World Foreign Lending*. For a given country i, we compute the total claims, both domestic and foreign, of all the countries other than country i. This serves as a proxy for all the money invested to the world excluding country i. It is a proxy because in order to obtain the exact number, we still need to a) substract from it the amount the rest of the world invested to countries i (included in the foreign lending of the other countries) and b) add to it the amount country i invested to other countries (country i's foreign lending). Since we do not have the liability side of the investment, a) is not directly computable. However, a) and b) being two measurement errors that go into opposite directions alleviates this measurement problem. Furthermore, if a countries foreign investment equals the foreign investment it receives, these two term can perfectly cancelled out.

In addition, we also look at several data on the potential factors that drive bank home bias, in particular uncertainty and banking sector characteristics. A more detailed explanation of the data sources can be found in Appendix 3.8.1.

Equity Besides the banking sector, we also apply the definition of home bias to countries' equity investment portfolios. The key data source used for equity is the Coordinated Portfolio Investment Survey from the IMF, which documents the holdings of foreign equity investment at the country level. Combined with data on domestic equity market capitalization obtained from the World Bank, we construct an annual home bias indicator for equity in the same way as bank home bias. The details of dataset construction can be found in Appendix 3.8.1.

Uncertainty Uncertainty is one of the key drivers for cross-border decisions that we want to examine [4] We adopt two measures from the literature to compute our uncertainty index. The first one is the Economic Policy Uncertainty Index (EPU), a comprehensive index of uncertainty based on news, tax code, and survey results developed by Baker et al. (2016). Although this index is available for over a dozen of countries, to ensure that we have the maximum data coverage, we also use the World Uncertainty Index (WUI) developed by Ahir et al. (2018). The dataset provides country-level data every month for over one hundred countries. Using this dataset, we can construct the domestic uncertainty index and foreign uncertainty index for each country.

Banking sector characteristics The last set of data is on banking sector characteristics, including banks' balance sheet size and composition, profitability, and capital ratios. For the United States, we obtain data from Federal Reserve Bank of New York's *Consolidated Financial Statistics for the U.S. Commercial Banking Industry* for an overview of the US banking sector. For European Union countries, we obtain similar data from European Central Bank Statistical Data Warehouse, in the dataset of *Consolidated Banking data*.

3.2.3 Stylized Facts

This section presents three main findings regarding country-level bank home bias. Additional results can be found in Appendix 3.8.3.

[4]The concept of uncertainty is sometimes used interchangeably with *risk*, as both concepts usually refer to the second-order moment of the stochastic distribution. In this research, we use the terminology *uncertainty*, as we want to capture a general reflection of the degree to which economic agents are unsure of future economic and policy outcomes, rather than the riskiness of the individual asset. The reason is that we want to capture the degree to which investors are not sure about the realization of investment returns, which depends.

Fact I: Bank home bias To start with, we want to see the general trend of bank home bias. The red line in Figure 3.1 displays the bank home bias for the United States and the black line is the weighted world bank home bias. The most salient feature we observe is a V-shaped trend. Before the Great Recession, US banks experienced a steady decrease in bank home bias. After the crisis, however, the trend reversed and returns to the original level in the early 2000s. The weighted world average of bank home bias shows a similar trend. These variations across time suggest that relative preferences for domestic lending are not constant, but rather a state-dependent reflection of various underlying economic forces.

Fact II: Bank vs. equity home bias In addition, we want to check whether the bank home bias exhibits patterns similar to capital home bias, in particular equity home bias. Using annual data, we compute country-level equity home bias and compare the results with bank home bias. Figure 3.2 displays the result. The details on the construction of equity home bias can be found in Appendix 3.8.1, and a panel table of country-wise equity home bias can be found in Appendix 3.8.1. From the figure, we see that weighted world bank home bias and weighted world equity home bias have similar trends prior to the Great Recession. After the recession, however, the trend continues for equity home bias but reverses for bank home bias.

The departure in the trends suggests that either bank home bias and equity home bias react differently to the same shock, or there are factors that affect only the banking sector but not equity. There are a few candidates. Firstly, major regulation reforms took place during and after the recession. The new Basel III regulatory framework, which specifies stringent capital requirements and liquidity requirements, could shift banks' attitudes toward cross-border lending. Secondly, the unprecedented scale of quantitative easing after the crisis might also cause bank investments and equity investments to move in different directions. While equity investments benefit from the expansionary monetary policy due to the appreciation of asset prices, bank investments, most of which are loans, are less liquid and often non-tradable. Moreover, due to interest rate pass-through rigidity, they experience a loss in profit if the deposit rate is rigid.

Fact III: Bank home bias and uncertainty We proceed to examine the driving forces of bank home bias, of which the first one is uncertainty. As stated in the previous section, we are interested in uncertainty as a measure of the overall investment environment. Therefore, instead of an asset-specific index like VIX, we use text-based measures, as bank assets consist of assets of broad categories. Figure 3.3 displays the result of plotting the weighted average world bank home bias against the weighted average Economic Policy Uncertainty (EPU) Index. The EPU is weighted in the same way as bank home bias and is shown with 4 quarters lag.

In the Figure, we see that the weighted bank home bias and the lagged weighted EPU index exhibit very similar patterns, in terms of both general trends and short-run variations. This indicates that uncertainty has strong predictive power of bank home bias, which is consistent with the intuition as uncertainty itself is a forward-looking index. Therefore, a high uncertainty level signals potential adjustment of the portfolios. Considering the maturity and liquidity structure of banks' portfolios, the adjustment is observed with a lag. In addition, we notice that the uncertainty index also remains high after the end of the Great Recession, the same as a prolonged period of high home bias. In Section **??**, we further investigate the role of uncertainty by decomposing it into domestic and foreign uncertainty and show that the latter turns out to be the most important one.

3.3 Drivers of Bank Home Bias: SVAR Analysis

In this section, we investigate the ain candidates for the driving factors of bank home bias variations, namely uncertainty and monetary policy, using the structural VAR (SVAR) approach. The goal is to provide causal evidence on the determinants of cross-border lending preferences by examining the impulse responses of bank home bias to identified shocks. We narrow our study to the case of the United States, for which we have rich data on banking sector characteristics. The following section discusses the other countries using panel data analysis.

3.3.1 Model Specification

The model is a standard vector autoregression model given by

$$\mathbf{y_t} = A_0 + A_1\mathbf{y_{t-1}} + \cdots + A_p\mathbf{y_{t-p}} + \mathbf{u_t} \quad t = 1, \cdots, T,$$

where y_t is an $k \times 1$ vector of endogenous variables, A_i are $k \times k$ coefficient matrices at lag i, and u_t are reduced-form errors. We assume that $u_t = \mathcal{S}\epsilon_t$, where ϵ_t is a vector containing structural shocks. Since structural shocks are assumed to be independent and of unit variance, the identification boils down to pinpoint the matrix $\mathcal{S}$, or a column of the matrix, so that we can perform analysis on the reaction of bank home bias to the structural shock. Therefore, the var-covar matrix of the residuals, Σ, is a matrix pinned down by $\Sigma = \mathcal{S}\mathcal{S}'$. Identifying structural shock can thus be achieved by exploiting the information in Σ.

3.3.2 Data Description

The sample period is from 2001 Q4 to 2019 Q4, stopping before 2020 to exclude the pandemic. The key variables in the model include bank home bias and the standard sets of macro variables: real GDP, Inflation, and monetary policy rate. Real GDP and Inflation are at a log level. Since our sample includes a zero federal funds rate period, we take the Wu-Xia shadow monetary policy rate developed by Wu and Xia (2016) as our monetary policy rate. Under this specification, the variables are given by $y_t = \{$*Real GDP*, *Inflation*, *Shadow Policy Rate*, *Bank Home Bias*$\}$. Since our data is in quarterly frequency, we take four lags, i.e., $p = 4$.

In addition to this baseline specification, we add to the model *Real Total Asset* and *Return on Asset*, which help capture the transmission channel of the monetary shock through banking sector characteristics. This augmented set of the variable for the identification of monetary policy shock would be $y_t = \{$*Real GDP*, *Inflation*, *Shadow Policy Rate*, *Real Total Asset of Banks*, *Return on Asset of Banks*, *Bank Home Bias*$\}$.

To identify uncertainty shocks, we add to the baseline specification two additional variables: *domestic uncertainty* and *foreign uncertainty*. The details on constructing domestic and foreign uncertainty can be found in Appendix **??**. The set of variables used for the identification of uncertainty shock is thus given by $y_t = \{$*Domestic Uncertainty*, *Foreign Uncertainty*, *Real GDP*, *Inflation*, *Shadow Policy Rate*, *Bank Home Bias*$\}$.

3.3.3 Uncertainty Shock

Identification

To identify uncertainty shock, we also use two identification methods to cross-check its validity. For the first method, we go for the similar set up of Bloom (2009) and make short run identification assumptions. Since this identification technique requires restricting the contemporaneous responses of variables, which might not be ideal for uncertainty indices as they contain forward looking component, we also go for a second identification method, namely the max share identification developed in Uhlig (2003).

Short-run Identification The identification assumption for the first approach is as follows. We assume that uncertainty shocks, due to its forward-looking nature, should instantaneously affects on the other variables, whereas the other shocks such as monetary policy shocks would not have a contemporaneous impact on uncertainty. This assumption requires that uncertainty variables is ranked at the beginning of the vector of variables. The respective column defined is obtained by doing Cholesky decomposition to the var-covariance matrix Σ.

Max-share Identification The identification assumption for the second approach is different from the first one in the sense that we do not put restrictions on the contemporaneous response. The aim is to identify a shock that has the maximum explanatory power over the forecast error variance decomposition. The shock identified is not independent from the other shocks in the sense that it can be the combination of multiple underlying shocks, since the only criterion is to identify the most influential shocks to uncertainty, or in our case, domestic uncertainty and foreign uncertainty respectively.

The identification proceeds as follows. We seek to pin down one column vector s^* from the $\mathcal{S}$ matrix which explains as much as possible of the forecast error variance of foreign uncertainty (respectively domestic uncertainty). However, instead of directly looping through all feasible vector to look for s^*, we obtain it indirectly by looking for a vector q of an orthonormal matrix Q, which is essentially a rotation matrix. Note that any matrix $\bar{\mathcal{S}}$ that satisfies $\Sigma = \bar{\mathcal{S}}\bar{\mathcal{S}}'$ can be represented as the multiplication of the Cholesky decomposition of Σ, denoted as $\mathbf{S}$, and an orthonormal matrix Q, i.e. $\tilde{\mathcal{S}} = \mathbf{S}Q$. The h step ahead forecast error of Y_t can thus be written as

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum_{l=0}^{h} A_l \mathbf{S} Q \epsilon_{t+h-l},$$

and the FEV share of variable i due to shock j at horizon h is given by

$$\Omega_{i,j}(h) = \frac{\sum_{l=0}^{h} A_{i,l}\mathbf{S}qq'\mathbf{S}'A'_{i,l}}{\sum_{l=0}^{h} A_{i,l}\Sigma_u A'_{i,l}}.$$

The identification goal is therefore to find a vector q that can explain the most of the FEV share of one shock up to k period,

$$\max_{q} \sum_{h=0}^{k} \Omega_{i,j}(h)_{ii}$$
$$\text{s.t.} \quad q'q = 1.$$

The optimal vector s^* is then pinned down by multiplying q with matrix $\mathbf{S}$, i.e. $s^* = \mathbf{S}q$.

In our result, we specify the maximization problem to be over one period (one quarter), and the results are robust to changing the maximization problem to longer periods. We apply this method to domestic and foreign uncertainty and obtain domestic uncertainty shock and foreign uncertainty shock respectively.

Results

We now proceed to the identification of uncertainty shocks. As we have discussed in previous section, uncertainty in our dataset is not one but two variables, since we decompose it into *Domestic Uncertainty* and *Foreign Uncertainty*. This decomposition allows us to pin down which uncertainty accounts for the more variations of home bias. The baseline identification method we use is short run identification method à la Bloom (2009), in which the uncertainty shock is assumed to be the only shock that can affect all the other variables contemporaneously. This assumption is consistent with the intuition, as uncertainty is a forward-looking variable that captures agents' expectation of future events. The second method we use is the max share identification à la Uhlig (2003). The idea is to identify uncertainty shock as the shock that can maximally explain the forecast error variances of the uncertainty indicator variable over certainty periods, so the identification method does no rely on particular assumption on the contemporaneous responses. As will be seen from the results, the results yield by these two identification methods do not differ by a large margin[5].

As it can be seen from Figure 3.4, we find that foreign uncertainty shock is a strong driver of bank home bias, inducing significant increase in bank home bias. The forecast error variance decomposition (FEVD) in Figure 3.5 shows that it explains up to half of the FEVD of bank home bias. The results are robust to replacing macro variables by balance sheet variables in the model. When applying the same identification method to domestic uncertainty shock, however, the response of bank home bias is not significant, as shown in Figure 3.6. This asymmetry responses to foreign and domestic uncertainty shock might be reconciled by the fact that

[5]More detailed explanation of the identification methods can be found in Appendix **??**.

domestic uncertainty shock induces both a substitution effect and a wealth effect effect. When foreign uncertainty goes up relative to domestic uncertainty, banks shift their investment to domestic market. However, when the domestic uncertainty is on a high level, presumably the overall financial situation faced by the banks also deteriorates. Therefore, although the substitution channel implies that more loans should be granted to foreign borrowers, the banks are not able to do so as the loan generating ability of the bank is compromised.

Discussion

As a robustness check, we again replace the macro variables with balance sheet components and check whether the home bias increase after foreign uncertainty shock is due to an increase in safe asset holdings. Figure 3.10 shows that an increase in home bias after a foreign uncertainty shock does not translate into an increase in Fed Funds and Reverse Repo holdings, and that loan level does not drop in response. This confirms that home bias again is not a direct reflection of asset category reshuffling, but rather a change in the preference for location.

3.3.4 Monetary Policy Shock

Identification

For monetary policy, we opt for two identification methods. The first one is the conventional Christiano et al. (1999) method of short run identification method. The second one is the proxy identification method introduced by Gertler and Karadi (2015).

Short-run Identification The first identification method relies on the recursive identification assumption that monetary policy shock does not have contemporaneous effect on output and inflation; or rather, monetary policy only responses contemporaneous to the shocks to these two macroeconomic variables. By this identification assumption, it suffices to assume that $\mathcal{S}$ is lower-triangular. It can thus be obtained by doing Cholesky decomposition to the matrix Σ.

Proxy Identification The assumption of short-run identification can be too restrictive, due to the fact that the contemporaneous responses from output and inflation to monetary policy might exist due to reasons such as the agents have forward-looking expectation regarding the factors that drive the monetary policy changes. Therefore, we adopt a second identification method, namely the proxy identification of monetary policy in Gertler and Karadi (2015).

The proxy identification method assumes the existence of an instrument variable Z_t, which satisfies

$$E\left[\mathbf{Z}_t \epsilon_t^{p'}\right] = \phi, \quad E\left[\mathbf{Z}_t \epsilon_t^{q'}\right] = \mathbf{0}$$

where $\epsilon_t^{p'}$ is the structural shock of interest, and $\epsilon_t^{q'}$ are all the other structural shocks. As shown by the equations, such an instrument variable can be used to identify the shock of interest as it is not correlated with other shocks. The key is thus to obtain a reliable proxy for monetary policy shock, and the authors argue that one ideal variable to serve this purpose is the policy news shock identified at very high frequency. Intuitively, around a thirty-minute window of Federal Reserve's policy announcement in the regular meetings by Federal Open Market Committee (FOMC), the responses of the various interest rates in the market should capture the full impact of the monetary policy change, given the fact that no economic fundamental would vary in such a short window. Therefore, the unexpected changes in the interest rates, in particular the fed funds future rates, captures the policy news shock. It serves as an ideal proxy for monetary policy shocks as it is exogenous to the system but highly correlated to the shock.

Since the data for proxy variables provided by Gertler and Karadi (2015) ends in the year 2012, we need access to a longer data period for high frequency data for the identification of monetary policy in our sample. To this end, we use an extended sample of monetary policy news shocks in Nakamura and Steinsson (2018), which contains the news shock obtained from fed funds future. We compare this sample with that of Gertler and Karadi (2015) and confirm that prior to 2012 the two data series are highly correlated, indicating that the same identification assumption should be valid throughout our data sample from 2000 to 2012. Note that in our sample, neither the short run identification method nor the proxy identification method yield the conventional responses of a monetary policy shock, i.e. it suppress output and inflation. This is due to the fact that our data sample contains a very special crisis period, in which unprecedented monetary expansion policies were implemented to combat the crisis, whereas monetary policy contraction is viewed as a strong signal for recovery. This is the potential cause for the unconventional responses from the economic variable. Once we restrict the sample to longer period pre-crisis, the results are the same as Gertler and Karadi (2015).

Results

We start with the identification of monetary policy shock. The baseline identification method we use is the short run identification à la Christiano et al. (1999). As a robustness check, we also use the proxy identification method of monetary policy shock developed by Gertler and Karadi (2015)[6].

The results, as shown in Figure 3.14, suggest that monetary policy shock first increases then suppresses bank home bias, implying that the impact of monetary policy on bank home bias might involve multiple channels. Part of the decrease in bank home bias, as suggested by the impulse response, might be due to an subsequent increase in bank profitability. The results still hold if we add banking sector characteristics as well as balance sheet decomposition. The forecast error variance decomposition and the robustness checks are given in Appendix **??**.

Discussion

As a robustness check, we replace the total asset variable by different components of the balance sheet. In particular, we want to study whether the initial increase in bank home bias is just due to an increase in the holdings of safe asset, indicating a shift in risk preferences rather than geographic preference. In Figure 3.16 in the appendix, we show the result of a monetary policy shock with the total real asset being replaced by two subcategories, namely *Loans* and *Fed Funds and Reverse Repos*. We see that the initial increase in bank home bias is not accompanied by a corresponding increase in Fed Funds; rather, when home bias goes down, the holding of Fed Funds goes up. On the contrary, Loans go up slightly on impact. These results imply that there is indeed a shifting in preferences for domestic versus foreign loans, rather that just a flight to safety.

3.4 Drivers of Bank Home Bias: Panel Analysis

This section generates the analysis on the drivers of bank home bias using US data to the panel of countries we have in the dataset. The key factors of interest are still uncertainty and monetary policy.

3.4.1 Home Bias and Uncertainty

To start with, we perform a panel regression analysis with the following specification

$$\text{hb}_{i,t} = \underbrace{\alpha_i}_{\text{country fixed effect}} + \underbrace{\beta \text{uncertainty}_{i,t}}_{\text{uncertainty index}} + \underbrace{\gamma X_{i,t}}_{\text{banking index}} + \underbrace{\theta Z_{i,t}}_{\text{other controls}} + e_{it} \,.$$

[6] More detailed explanation on the identification scheme can be found in Appendix **??**.

The dependent variable is the bank home bias. To test for Granger Predictability, we also use bank home bias that leads one period ahead, $\text{hb}_{i,t+1}$. The explanatory variable includes uncertainty indices, which consist of a country-level uncertainty index and a world-average uncertainty index. We add the world-average uncertainty because we want to use this variable to proxy *foreign* uncertainty, which potentially matters more for home bias than domestic uncertainty, as shown in the previous section. In addition to uncertainty, we control for banking sector characteristics captured by bank sizes and economic conditions captured by GDP, inflation, and stock market index. Since our explanatory variable includes a term common to all countries, the average world uncertainty, we add only the country-fixed effect and not the time-fixed effect.

The results are shown in Table 3.2 and 3.2. As can be seen from the table, the average world uncertainty index is positively correlated with bank home bias, and the coefficient is significant in all specifications. On the contrary, domestic uncertainty is positively correlated with home bias, but the effect becomes smaller and less significant with more controls. The results are in line with the country-level analysis in the SVAR exercises. Note that the interaction term of the two is always significant. That is, the impact of a higher foreign uncertainty is attenuated by the presence of a higher domestic uncertainty, which is consistent with intuition. The rest of the control variables are also in line with the expectation: A better economic condition (as reflected by higher GDP and inflation) leads to higher home bias, and a stronger financial sector (as reflected by larger bank sizes and higher share prices) decreases home bias. As a next step, we plan to construct for each country their specific foreign uncertainty index instead of using the average uncertainty for all countries.

3.4.2 Home Bias and Monetary Policy

To test for the effect of monetary policy, we adopt a similar specification as in the uncertainty model, with an additional monetary policy index.

$$\text{hb}_{i,t+1} = \alpha_i + \underbrace{\beta \text{uncertainty}_{i,t}}_{\text{uncertainty index}} + \underbrace{\eta i_{i,t}}_{\text{monetary index}} + \underbrace{\gamma X_{i,t}}_{\text{banking index}} + \underbrace{\theta Z_{i,t}}_{\text{other controls}} + e_{it} \,.$$

Since our sample periods span the post-crisis era, we need to collect proxy variables for the monetary policy rates of all the countries that experienced the zero lower bound period. As a preliminary test, we adopt one uniform monetary policy rate index for all countries: the shadow rate of the US monetary policy. In addition, we use an alternative uncertainty index, the *Economic Policy Uncertainty (EPU)*, when measuring the world uncertainty.

The results in Table 3.3 show that most of the findings align with the previous specification. The new variable of interest, namely the US shadow rate, has a negative impact on bank home bias. That is, when the interest rate goes up, banks tend to diversify more across countries. In the country-level SVAR exercise, we show that the response can arise from the impact of monetary policy rate increase on asset returns and bank profitability. In the next step, we will incorporate country-specific shadow rates and examine the mechanisms of asset returns and profitability in the panel regression.

3.5 Cyclicality of Home Bias

This section investigates the economic consequences of bank home bias variations by examining the cyclicality of banks' home bias patterns. That is the extent to which these investment patterns vary with the economic cycle.

The relationship between economic performance and bank home bias can be complicated, as it involves two opposite effects: the substitution effect and the wealth effect. For the substitute effect, during economic expansions, banks tend to be more optimistic about the prospects of their home economy and are, therefore, more likely to invest in domestic assets. As a result, bank home bias becomes higher during periods of economic expansion. On the other hand, during economic contractions or recessions, banks become more risk-averse and tend to reduce their exposure to domestic assets. Thus, bank home bias tends to be less pronounced during periods of economic contraction. For the wealth effect, the mechanism works in the opposite direction. During economic booms, banks earn more profits and build up their capital buffer, allowing them to perform riskier investments at a farther distance, thereby decreasing banks' home bias. On the contrary, domestic banks face tightened liquidity environment and high domestic uncertainty during the economic downturn, undermining their ability to lend overseas.

Therefore, an alternative way to interpret the two effects is from the demand and supply of credit. From the demand side of credit, domestic economic booms imply higher demand for credit from domestic borrowers, which causes the banks to reallocate their investments. From the supply side, a better economic situation expands banks' credit supply, which can extend to banks' overseas lending and thereby decreases banks' home bias.

The cyclically of bank home bias patterns has important implications for the stability of financial markets and the overall economy. When banks invest a significant portion of their assets in foreign markets, they can also become highly influential in the economic conditions of the foreign country. This can lead to a situation where a downturn in the domestic economy can severely impact the banking sector, causing it to decrease its foreign lending, which in turn leads to a recession in foreign economies. Therefore, policymakers need to be aware of the cyclical nature of bank home bias and take appropriate measures to mitigate its associated risks.

3.5.1 Correlation between Cyclical Components

We start by extracting the cyclical component of the time series of interest, namely the country-level bank home bias and GDP, and examine the correlation between the cyclical component. Given that a time series can be decomposed into the sum of a cyclical component and a trend component, $y_{i,t} = y_{i,t,cyclical} + y_{i,t,trend}$, we follow the procedure below and perform the analysis on sub-groups of the countries in our sample.

1. Apply bandpass filter $B(p_{min}, p_{max})$ à la Baxter-King to $y_{i,t}$.
2. Obtain cyclical and trend component $(y_{i,t,cyclical}, y_{i,t,trend})$.
3. Compute percentage deviation from trend $\xi_{i,t,dev} = \frac{y_{i,t,cyclical}}{y_{i,t,trend}}$.
4. Conduct steps 1.-3. for another time series to obtain $\psi_{i,t,dev}$.
5. Compute correlation between $(\xi_{i,t-h,dev}, \psi_{i,t,dev})$ for $h \in [\bar{h}, \ldots, 0]$.
6. Construct weights ω_i and compute weighted correlation for regions.

We define the filtering frequencies as high frequency as $B(6, 32)$ and medium frequency as $B(32, 80)$. The results are shown in Table 3.4.

3.5.2 Granger Predictability

We now run the Granger predictability test with the following econometric specification

$$\text{hb}_{i,t} = \underbrace{\alpha_i}_{\text{country fixed effect}} + \underbrace{\gamma_t}_{\text{time fixed effect}} + \beta_1 \Delta \text{gdp}_{i,t-1} + \beta_2 d_{\textit{pre-crisis},t} + e_{it} \ .$$

where $\Delta \text{gdp}_{i,t-1}$ is lagged GDP growth, and $\beta_2 d_{pre\text{-}crisis,t}$ is a dummy variable that takes on the value of one before the Great Recession and zero afterwards. In this specification, we use a purely backward-looking filter. This specification allows us to examine the Granger predictability of GDP on bank home bias. With country-fixed effects, we control asset trade costs. With time-fixed effects, control for hedging motives. The results are shown in Table 3.5.

From the table, the variable lagged GDP growth always positively impacts bank home bias, which favors the demand side mechanism. Nevertheless, once we include the impact of the crisis by incorporating the crisis dummy, we can see that the overall impact of GDP growth becomes negative. The difference shows that prior to the crisis, higher GDP growth is always associated with less bank home bias, implying that the supply-side mechanism works. Comparing the pre- and post-crisis patterns, we can see that domestic economic growth no longer boosts domestic banks' foreign lending. The results suggest a structural break in the banking sector or the banks' lending patterns, of which one potential reason is the low-interest rate period after the recession.

Nevertheless, the Granger predictability test has limitations. First, the country $i's$ GDP growth may correlate with counterparty countries' GDP growth, i.e., a decrease in home bias may reflect that the other country's GDP is high. Second, the regression might inhabit reversed causality. The variations in bank home bias, which drives the cross-border capital flows, can also contribute to countries' GDP growth. To alleviate these issues, we also run fixed effect regression on first differences, use real GDP growth, and check for the persistence of home bias. The results are robust to these changes.

3.5.3 Dynamic Panel Model

To further examine the relationship between domestic economy and bank home bias, we run a dynamic panel model of the following form

$$hb_{i,t} = \alpha_i + \gamma_t + hb_{i,t-1} + \beta_1 \Delta \text{gdp}_{i,t-1} + e_{it} \ .$$

With the dynamic panel setup, we take into consideration the persistence in GDP growth rates and bank home bias. The results are shown in Table 3.6. We can see that home bias exhibits high persistence. Once we control for this persistence, the impact of lagged GDP growth on bank home bias becomes negative, indicating that the wealth effect dominates the substitute effect in banks' investment decisions. However, once we control for the time-fixed effect, the impact of GDP growth becomes insignificant.

3.5.4 Panel VAR

In the previous analysis, we focused on the effect of GDP on the home bias. In order to study the inverse relationship, we use a standard panel VAR model in Holtz-Eakin et al. (1988)

$$y_{i,t} = \alpha_i + \sum_{l=1}^{p} A_l y_{i,t-l} + B x_{i,t} + \epsilon_{i,t} \ ,$$

where $y_{i,t}$ is a vector of endogenous variables and $x_{i,t}$ a vector of exogenous variables. The results are shown in Table 3.7.

From the table, we can see that the size and the sign of the coefficient of lagged GDP growth on bank home bias are similar to that of the dynamic panel model, except that the sign becomes weakly significant even for real GDP growth. For the other direction, i.e., the impact of home bias on GDP, we see that home bias lag positively impacts GDP growth in nominal and real terms. This is consistent with our intuition, as a higher home bias indicates banks supply relatively more credit to domestic borrowers than foreign ones. It is associated with higher GDP if more credit translates to higher investment, boosting economic growth. The results confirm our hypothesis that the domestic economy can be dynamically affected by banks' international allocation of credit supply, and the domestic economy has international spillover via global bank lending. In the case of a regional economy where the member countries' banking sector are closely connected, for instance, a monetary union, the consequences are two-fold. On the one hand, a domestic economic boost can lead to a higher credit supply to foreign countries, fueling the region's economic growth. On the other hand, when a negative shock hits the country and experiences a recession, home bias increases. Rebalancing of banks' portfolios serves as an automatic stabilizer for domestic countries. However, it can exacerbate the situation in foreign countries and dampen the recovery speed for the whole region if the response is reciprocal and other countries' banks also pull from the home country.

The limitation of this panel VAR model is straightforward. Although our sample includes many countries, the model does not explore interdependence across countries. That is, how foreign countries' GDP affects domestic bank home bias. In reality, this is likely the scenario. For instance, the home bias of the capital-rich countries can directly impact the less developed countries. When rich countries experience an economic downturn, forcing their banks to retreat from less developed countries, banks of these countries have to take similar action to meet the gap between credit demand and supply in their domestic countries. As a next step, we will put assumptions on the structure of the error terms of the panel VAR models to study the interdependence across countries.

3.6 Conclusion

In this paper, we build a bank home index on a country level for over thirty countries, document home bias variations for the past two decades, and provide empirical analyses of the driving factors and their economic consequences. Our findings show that the home bias of banks exhibits substantial variation across time. It is heavily affected by uncertainty in the global environment and the monetary policy rate. Regarding the economic consequences, our results show that bank home bias is highly counter-cyclical. While cyclicality means that banks adjusting their portfolio allocation might be an automatic stabilizer for the domestic economy, it can potentially lead to a prolonged period of recession for the regional economy if all countries' banks respond by pulling off from foreign investment.

As a next step, we plan to establish further the links between banks' home bias and the real economy and examine the impact of banks' portfolio adjustment on domestic and foreign economies. First, we will investigate the potential structural break caused by the Great Recession and provide evidence of the lending preference of the banking sector changes after the recession. Second, we will exploit the inter-connectedness between different countries' home bias and GDP by imposing more structural on the residuals of the panel VAR to obtain causal identification of the impact of bank home bias variations on both domestic and foreign economies.

3.7 Figures and Tables

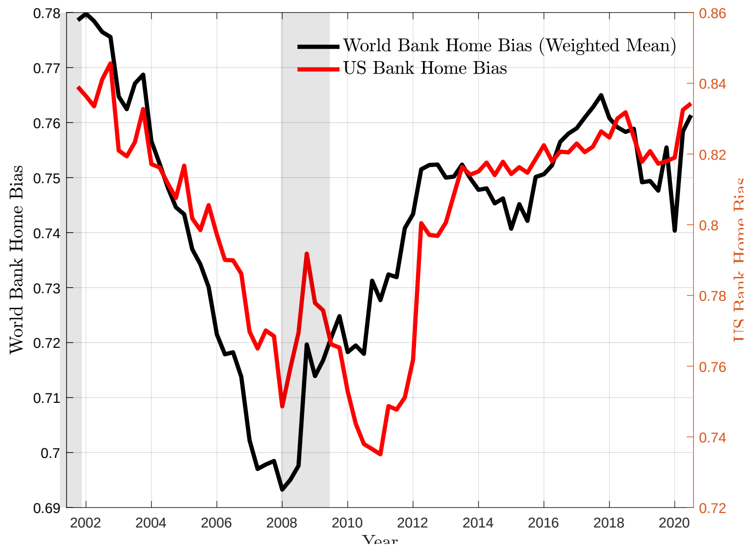

Figure 3.1: Bank Home Bias Fluctuations.

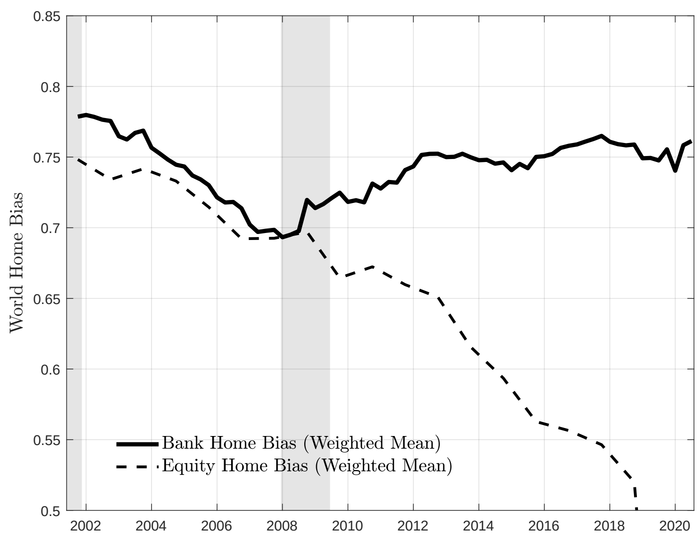

Figure 3.2: World Bank home bias vs. World equity home bias.

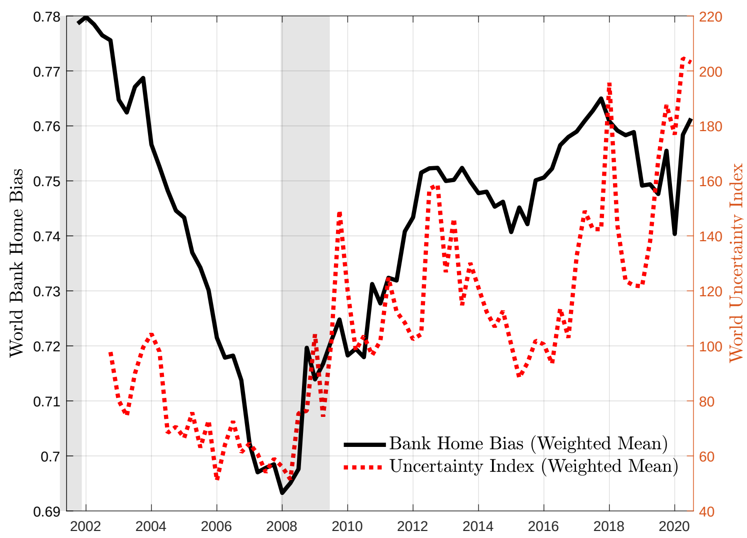

Figure 3.3: Weighted Mean of World Bank Home Bias and Uncertainty.

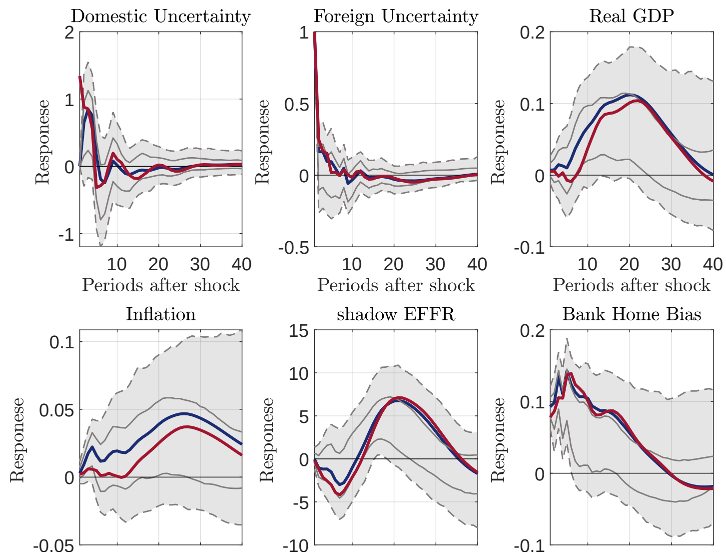

Figure 3.4: Impulse Response to foreign uncertainty shock.

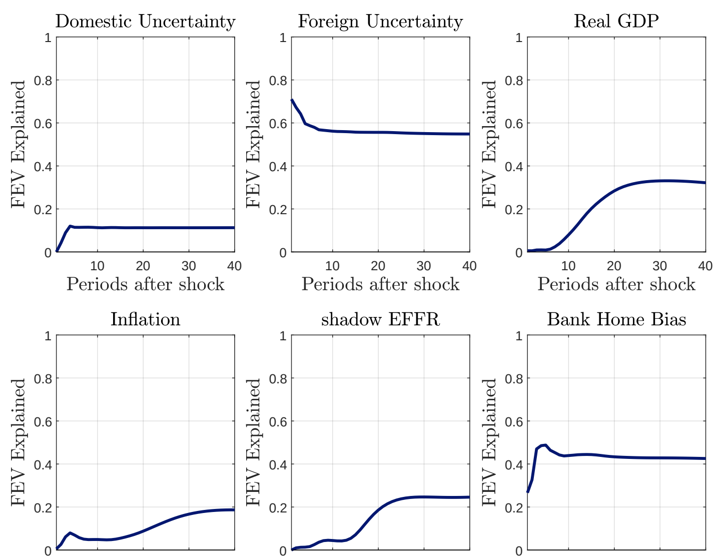

Figure 3.5: FEVD to foreign uncertainty shock.

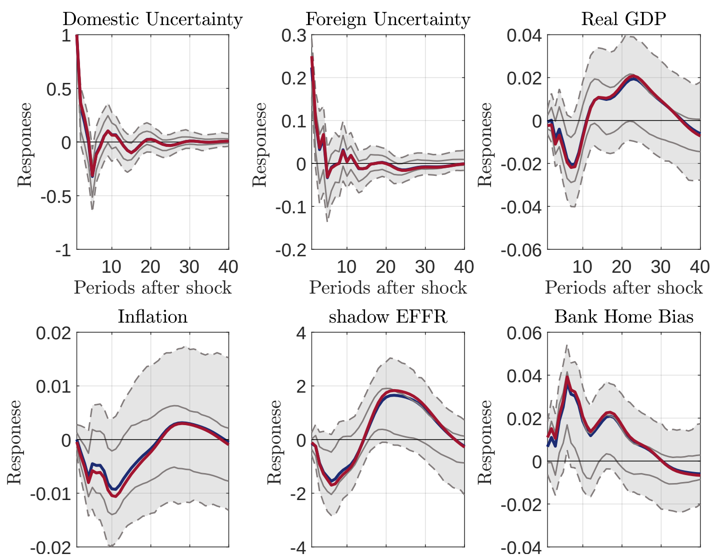

Figure 3.6: Impulse Response to foreign uncertainty shock.

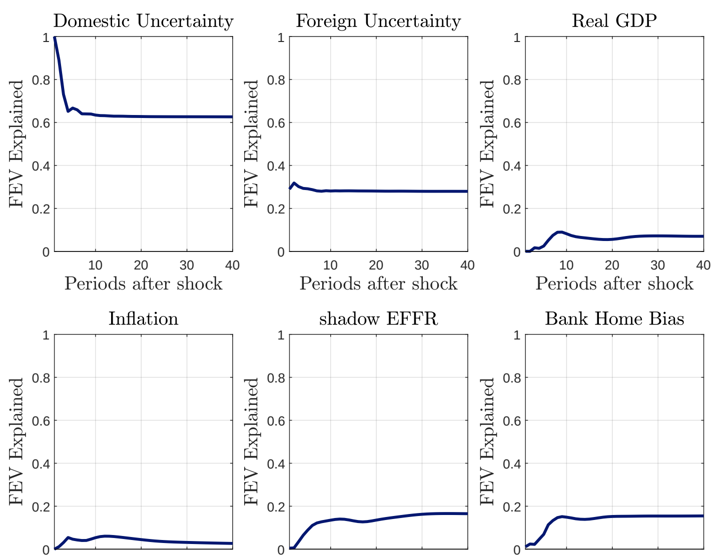

Figure 3.7: FEVD to foreign uncertainty shock.

Impulse responses of uncertainty shock: With only key variable.

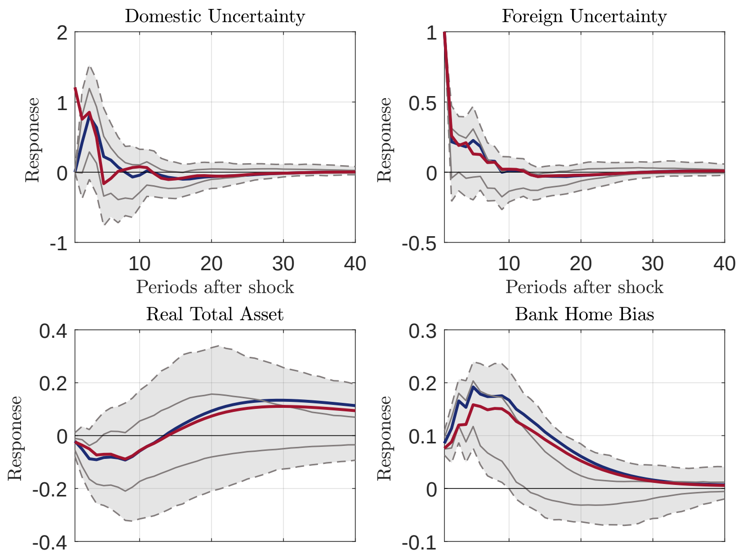

Figure 3.8: Impulse Response to foreign uncertainty shock.

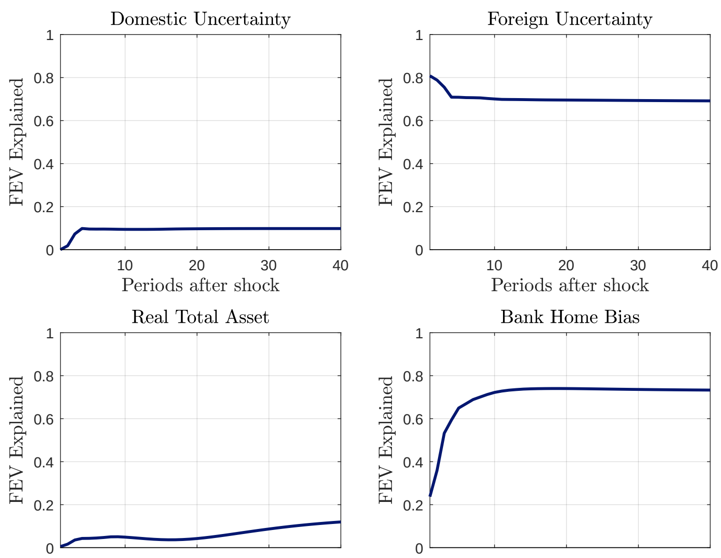

Figure 3.9: FEVD to foreign uncertainty shock.

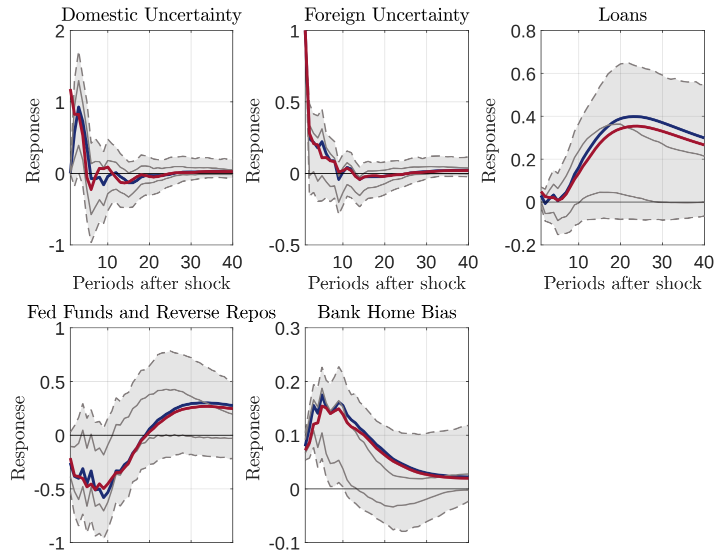

Figure 3.10: Impulse Response to foreign uncertainty shock.

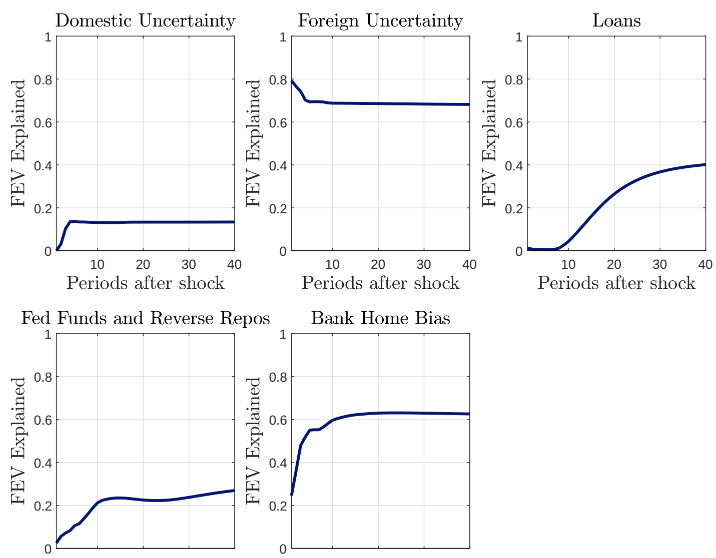

Figure 3.11: FEVD to foreign uncertainty shock.

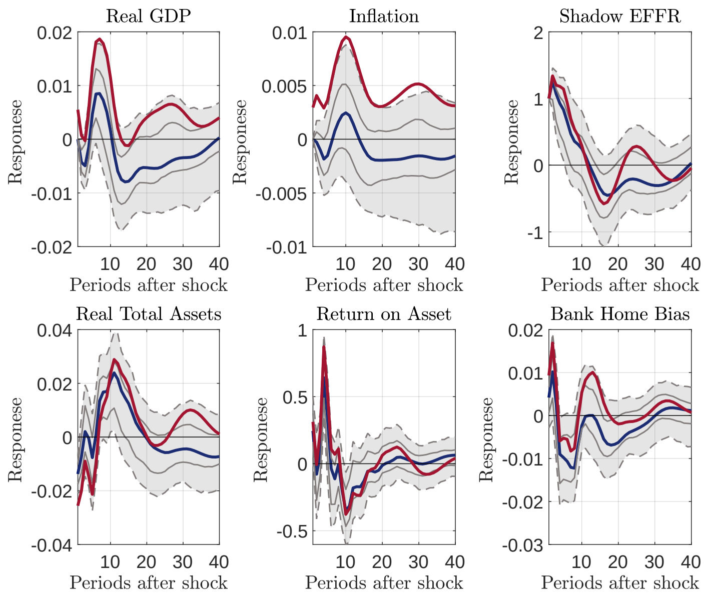

Figure 3.12: Impulse Response to monetary shock.

Notes: Blue line is the impulse responses from short run identification. Shaded area is 95% confidence level. Red line is the impulse responses from proxy identification. Sample period is from 2001 Q3 to 2019 Q3.

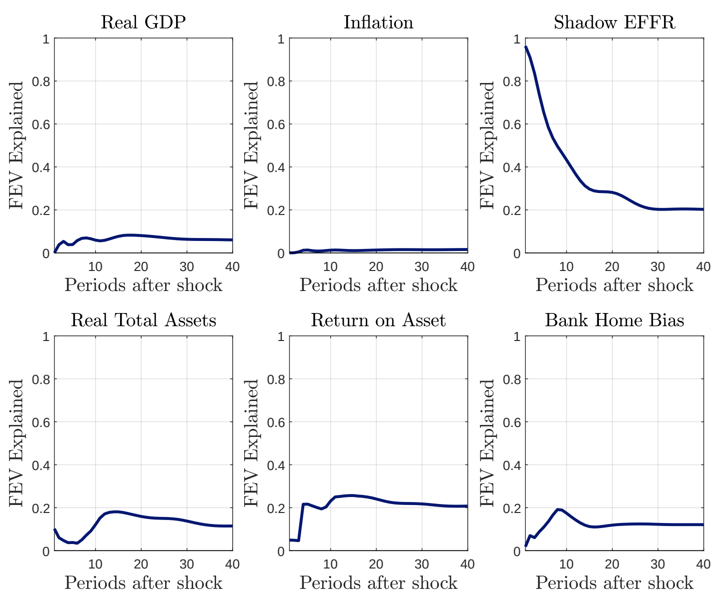

Figure 3.13: FEVD to monetary shock.

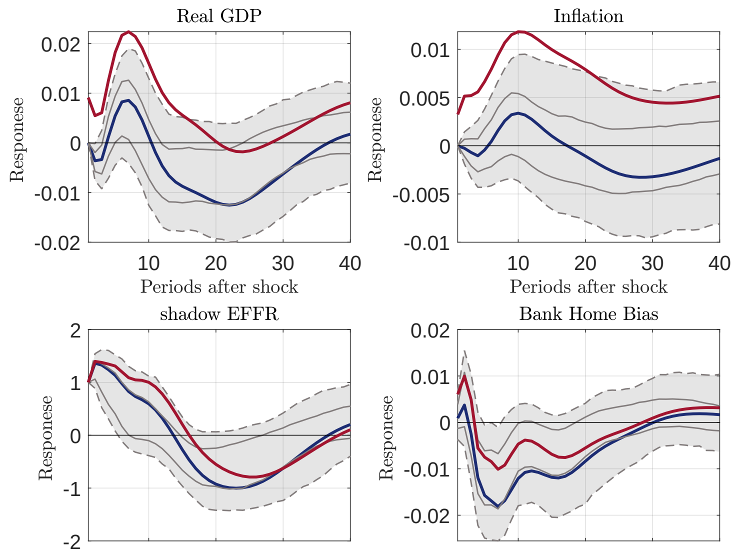

Figure 3.14: Impulse Response to monetary shock.

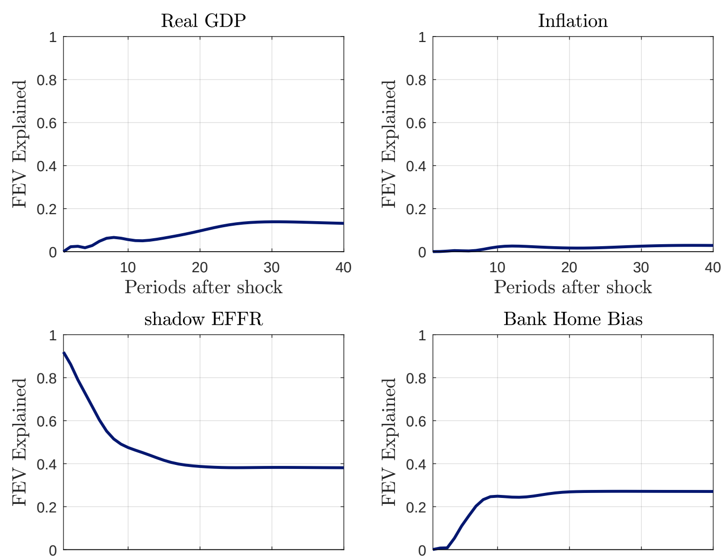

Figure 3.15: FEVD to foreign monetary shock.

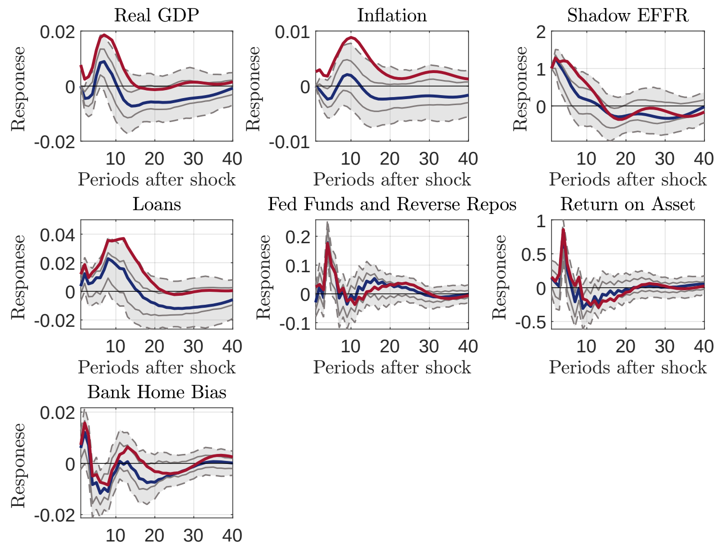

Figure 3.16: Impulse Response to monetary shock.

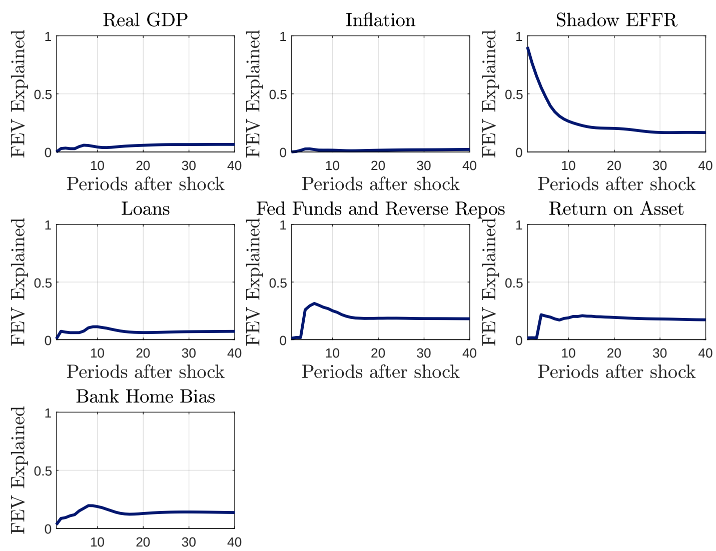

Figure 3.17: Impulse Response to monetary shock.

	Dependent variable			
	Home Bias *t*			
	(1)	(2)	(3)	(4)
World Avg Uncertainty (ww WUI)	**0.084*****	**0.141*****	**0.142*****	**0.133*****
	(0.026)	(0.025)	(0.026)	(0.026)
Domestic Uncertainty (WUI)	0.034*	0.034*	0.041**	0.023
	(0.019)	(0.018)	(0.018)	(0.018)
ln (total bank claims in usd)		**-0.036*****	**-0.126*****	**-0.141*****
		(0.003)	(0.006)	(0.006)
ln (real gdp in usd)			0.121***	0.159***
			(0.009)	(0.010)
ln (gdp deflator)			0.175***	0.270***
			(0.014)	(0.016)
ln (share prices)				-0.042***
				(0.004)
mean (ww WUI) $\times$WUI	**-0.139***	**-0.154****	**-0.224*****	**-0.187****
	(0.078)	(0.074)	(0.075)	(0.074)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Number Countries	28	28	25	24
Observations	1,668	1,668	1,532	1,475
R^2	0.008	0.105	0.278	0.337
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 3.1: Bank Home Bias and Uncertainty

	Dependent variable			
	Home Bias *(leading one period)*			
	(1)	(2)	(3)	(4)
World Avg Uncertainty (ww WUI)	**0.106*****	**0.161*****	**0.164*****	**0.152*****
	(0.027)	(0.026)	(0.027)	(0.027)
Domestic Uncertainty (WUI)	0.038**	0.038**	0.041**	0.021
	(0.019)	(0.018)	(0.018)	(0.018)
ln (total bank claims in usd)		**-0.035*****	**-0.117*****	**-0.134*****
		(0.003)	(0.006)	(0.006)
ln (real gdp in usd)			0.109***	0.150***
			(0.009)	(0.010)
ln (gdp deflator)			0.161***	0.259***
			(0.014)	(0.016)
ln (share prices)				-0.043***
				(0.004)
mean (ww WUI) $\times$WUI	**-0.158****	**-0.177****	**-0.222*****	**-0.177****
	(0.079)	(0.075)	(0.077)	(0.077)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Number Countries	28	28	25	24
Observations	1,640	1,640	1,509	1,453
R^2	0.013	0.106	0.252	0.314
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 3.2: Leading Bank Home Bias and Uncertainty

	Dependent variable:	
	Home Bias *(leading one period)*	
	(1)	(2)
ln (total bank claims in usd)	−0.124***	−0.125***
	(0.006)	(0.006)
World Avg Uncertainty (ww EPU)	0.0001***	0.0002***
	(0.00002)	(0.00003)
Domestic Uncertainty (WUI)	−0.013**	0.034**
	(0.006)	(0.015)
ln (real gdp in usd)	0.107***	0.109***
	(0.008)	(0.008)
ln (gdp deflator)	0.187***	0.189***
	(0.012)	(0.012)
ln (share prices)	−0.00002	−0.00002
	(0.00003)	(0.00003)
shadow rate	−0.004***	−0.004***
	(0.001)	(0.001)
mean_EPU × WUI		−0.0003***
		(0.0001)
Country FE	*Yes*	*Yes*
Time FE	*No*	*No*
Number Countries	25	25
Observations	1,677	1,677
R^2	0.249	0.254
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.3: Bank Home Bias and Monetary Policy

	Correlations weighted by region				
	$\rho(gdp_{t-4}, hb_t)$	$\rho(gdp_{t-3}, hb_t)$	$\rho(gdp_{t-2}, hb_t)$	$\rho(gdp_{t-1}, hb_t)$	$\rho(gdp_t, hb_t)$
Asia	-0.03	-0.09	-0.16	-0.21	**-0.28**
North EZ	0.24	0.21	0.03	-0.16	**-0.25**
South EZ	-0.09	-0.08	-0.09	-0.08	0.00
North America	0.15	0.11	0.12	-0.02	**-0.33**
South America	-0.20	-0.32	-0.24	0.02	0.27
World	0.10	0.06	-0.01	-0.12	**-0.23**

Table 3.4: Correlation of cyclical components of real gdp and bank home bias.

	Dependent variable:			
	Home Bias			
	(1)	(2)	(3)	(4)
gGDP Lag	0.449∗∗∗	0.329∗∗	0.490∗∗∗	0.325∗∗
	(0.154)	(0.119)	(0.154)	(0.158)
gGDP Lag × Crisis	−0.431∗∗	−0.537∗	−0.540∗∗	−0.659∗∗
	(0.224)	(0.281)	(0.224)	(0.278)
GDP Level			−0.000∗∗	−0.000∗∗∗
			(0.000)	(0.000)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Number Countries	24	24	24	24
Observations	1,484	1,484	1,484	1,484
R^2	0.006	0.004	0.017	0.035
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.5: Home bias in total bank assets and the business cycle.

	Dependent variable:	
	Home Bias	
	(1)	(2)
Home Bias Lag	0.957∗∗∗	0.959∗∗∗
	(0.007)	(0.008)
GDP Growth Lag	−0.072∗∗	−0.058
	(0.035)	(0.038)
Country FE	Yes	Yes
Time FE	No	Yes
Number Countries	24	24
Observations	1,484	1,484
R^2	0.918	0.917
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3.6: Home bias in total bank assets and the business cycle.

	Dependent variable:			
	Nominal GDP		*Real GDP*	
	Home Bias	GDP Growth	Home Bias	GDP Growth
Home Bias Lag	0.959∗∗∗	0.020∗∗	0.958∗∗∗	0.020**
	(0.007)	(0.007)	(0.008)	(0.006)
GDP Growth Lag	−0.070∗∗	0.162∗∗∗	−0.068∗	0.042
	(0.027)	(0.026)	(0.033)	(0.026)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number Countries	25	25	24	24
Observations	1,593	1,593	1,528	1,528
Note:				*p<0.05; **p<0.01;***p<0.001

Table 3.7: Panel VAR estimation for nominal and real gdp growth.

3.8 Appendix

3.8.1 Additional Data Source

Data for Equity Home Bias

Construction of cross-border investment. For cross-border investment, we use data from Coordinated Portfolio Investment Survey (CPIS) dataset developed by IMF. The dataset gives detailed decomposition of each country's foreign equity holding on a yearly basis, and one can specify both the origin and destination of the investment. Therefore, we can directly compute each countries' asset holding by specifying the recipient to be the rest of the world.

Construction of domestic investment. To compute the size of domestic investment, i.e. domestic investors' holding of domestic equities, we proceed in three steps. Take country i for example. First, we collect data on the stock market capitalization of country i, which is the total size of its stock market. Second, we compute how much of country i's equity is held by foreign investors. This is done by aggregating over all the other countries' holding of country i's equity. Lastly, we obtain domestic investor's holding of domestic equity as the difference between the two.

The stock market capitalization data is obtained from the World Bank. Two data series are used to construct this sample, namely *Market capitalization of listed domestic companies (% of GDP)* and *Stock Market Capitalization To GDP (%)*. The former stops at the year 2017, while the latter have data up until 2019. However, the latter time series has missing value at the beginning of the sample period. The values of these two series do not differ by a very large amount. Therefore, for each country, we compare the data from these two sources and choose the one with longer available periods to ensure largest possible coverage. We then multiply this ratio with GDP data to obtain the final values.

Since the construction of home bias requires a clear definition of the *world* as a benchmark,

Construction of equity home bias. Recall that the construction of home bias requires a clear definition of the *world* as the benchmark. In the case of equity home bias, after obtaining data from World Bank and IMF and merging the datasets, we obtain a final dataset of 41 countries, which contains all the 32 countries in our bank home bias dataset except for three countries: Bahamas, South Korea, and Russia. However, many of these countries contain long period of missing values and might render the weighted average computation unreliable. Therefore, we reduce this large sample to a smaller one in which all countries have complete data until 2018. The sample consists of 26 countries, and contains all the 32 countries in bank home bias dataset except for 7 countries: Bahamas, Cyprus, Denmark, Finland, Italy, South Korea, Netherlands, Russia, and Sweden. We refer to the former one as large sample, and the latter as small sample. We use small sample for the computation of our equity home bias and keep the large sample to check the robustness.

To obtain the equity home bias, again we need to compute

$$\text{Home Bias of Country } i = 1 - \frac{A_i}{B_i}.$$

For A_i, the computation is done by dividing total cross-border equity holding with the sum of cross-border and domestic equity holding. For B_i, the computation method is the same as that of bank home bias.

Data for Uncertainty

World uncertainty index. The main dataset we use to capture uncertainty is the World Uncertainty Index (WUI) developed by Ahir et al. (2018), an index based on word-counting method and is available for many countries in the world. As one of our goal is to distinguish domestic uncertainty from foreign uncertainty, the broad coverage of this measure proves to be crucial for our research. We take the World Uncertainty Index measurement for country i as the *domestic uncertainty* indicator. For *foreign uncertainty*, we construct it in two different methods. The first method is to compute directly the weighted world average uncertainty without country i as the foreign uncertainty for country i. The second method is to regress the total weighted world average uncertainty on country i's uncertainty and take the residual to be the foreign uncertainty to country i. The latter methods by construction generates foreign uncertainty that is uncorrelated to domestic uncertainty, while the former allows for correlation between domestic and foreign uncertainty. For the U.S., foreign uncertainty pinned down by the two methods are highly correlated. For smaller countries, these two measures might differ by a larger margin.

Economic policy uncertainty index. Economic Policy Uncertainty (EPU) index, developed by Baker et al. (2016), is an index based on newspaper coverage frequency. The data is available for less countries than World Uncertainty Index, so we keep it as our secondary measure for domestic and world uncertainty.

Other uncertainty measurement. For the United States, we have more detailed available measurement of domestic uncertainty, including Jurado et al. (2015)'s uncertainty measurement, and Berger et al. (2020)'s measurement of implied volatility.

3.8.2 Bank Home Bias Index

Illustration of the Index

In order to illustrate the bank home bias index, we use the subsequent two country example. The pie chart in Figure 3.18 displays the composition of the total worldwide investment, where investment into the domestic country A is colored in blue and that into the foreign country B in yellow. Out of the total investment, the part financed by country A's banks is the part inside the inner circle. In other words, the size of the inner circle reflects the size of total assets of country A's banks. We can see that part of their investment goes into the domestic country (the blue part), and the remainder goes into foreign country (the yellow part). The outer part of the circle is the investment of county B's bank, which also consists of investment into both countries.

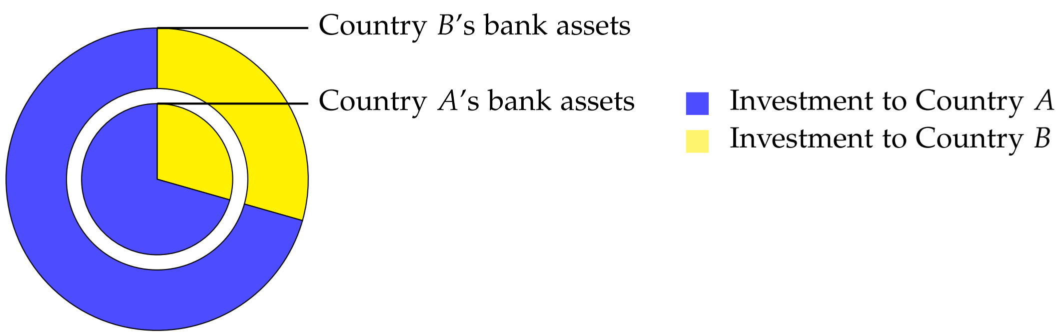

Figure 3.18: Illustration of Zero Home Bias based on Two Country Example.

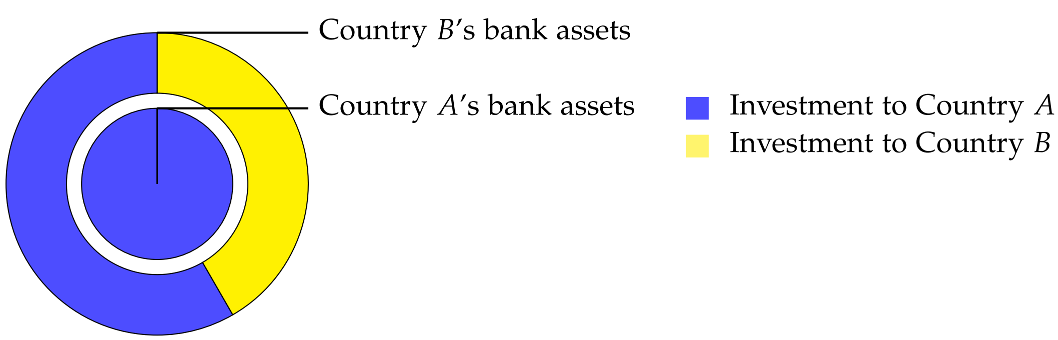

Figure 3.19: Illustration of Unit Home Bias based on Two Country Example.

Had country A's bank exhibited no home bias, the composition of bank asset portfolio should be the same as the world's composition. This is exactly the case in Figure 3.18, as the ratio between domestic investment and foreign investment inside the circle is exactly the same as the composition of the world. However, if domestic banks have perfect home bias, their assets could be completely invested into domestic country. As can be seen in Figure 3.19, the inner circle now contains only the blue part, indicating that all of country A's banks' assets are domestic. Country B's total bank assets, represented by the outer part of the circle, are still divided into a blue and a yellow part, indicating that country B's banks still diversify their investments.

According to equation (3.2.1), home bias of country A is defined as

$$\mathcal{HB}_A = 1 - \frac{\frac{A_f}{A_d + A_f}}{\frac{A_f + B_d}{B_d + B_f + A_d + A_f}},$$

where A_f denotes the investment into country A financed by country B' banks (the blue part in the inner circle in Figure 3.18), and A_d by the domestic bank (the blue part in the inner circle in Figure 3.18). Correspondingly, B_f is the investment to country B financed by country A, and B_d is financed by country B.[7]

Computation Results

See in next pages.

[7]Note that an alternative way to define the home bias index is based on comparing to what extent the domestic investment share is too high in domestic country's bank assets. The definition is given by

$$\mathcal{HB}_d' = \frac{\frac{A_d}{A_d + A_f}}{\frac{A_d + B_f}{B_d + B_f + A_d + A_f}} - 1.$$

The two measures can be linked by the relationship

$$\mathcal{HB}_d' = \frac{S}{1 - S} \mathcal{HB}_d.$$

where $S = \frac{B_d + A_f}{B_d + B_f + A_d + A_f}$ is the ratio of investment into the foreign country relative to the worldwide investment. This dual index reflects the flip side of high bank home bias: foreign assets being underrepresented in domestic bank's asset portfolio implies that domestic banks have an overly large market share within the domestic country. This can be seen by comparing Figure 3.18 and Figure 3.19, the latter of which shows that country A's own banking sector is the only creditor to country A's investments. The consequences are twofold. First of all, a high market share may lead to a higher market power. Here we treat the competition within the domestic banking sector as constant, i.e. there are no bank mergers or new entrants, resulting in a different degree of interest rate pass-through. Second of all, a high reliance on domestic banks over-proportionally exposes the country's economy to domestic banking sector risk. If the domestic banking sector experiences negative shocks, e.g. an exogenous shock that destroys bank capital, the impact on the real economy could be substantially larger than in the case in which there is low home bias.

Table 3.8: Annual Bank Home Bias.

Sample / Time	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
By Country																			
Australia	0.91	0.90	0.87	0.88	0.87	0.87	0.86	0.87	0.89	0.87	0.86	0.86	0.86	0.82	0.83	0.85	0.84	0.84	0.84
Austria	0.70	0.69	0.68	0.60	0.56	0.52	0.50	0.53	0.55	0.56	0.60	0.61	0.62	0.64	0.65	0.67	0.68	0.67	0.68
Bahamas									0.01	0.01	0.02	0.03	0.05	0.06	0.06	0.07	0.06	0.06	0.06
Belgium	0.43	0.41	0.37	0.33	0.34	0.32	0.33	0.39	0.42	0.44	0.46	0.47	0.47	0.52	0.53	0.57	0.60	0.59	0.60
Brazil		0.96	0.96	0.97	0.96	0.96	0.95	0.97	0.97	0.97	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.96	0.96
Canada	0.90	0.90	0.90	0.90	0.89	0.88	0.87												
Chile		0.93	0.97	0.96	0.96	0.96	0.95	0.96	0.97	0.95	0.95	0.95	0.94	0.93	0.93	0.95	0.95	0.94	0.91
Cyprus								0.40	0.41	0.47	0.51	0.65	0.69	0.68	0.73	0.74	0.75	0.73	0.70
Denmark	0.83	0.81	0.81	0.81	0.80	0.78	0.79	0.81	0.82	0.84	0.83	0.80	0.75	0.75	0.74	0.74	0.76	0.74	0.71
Finland	0.66	0.72	0.72	0.76	0.74	0.74	0.74	0.76	0.63	0.54	0.58	0.56	0.54	0.56	0.62	0.81	0.77	0.62	0.63
France	0.66	0.65	0.59	0.54	0.52	0.54	0.56	0.58	0.58	0.59	0.61	0.60	0.59	0.60	0.61	0.62	0.58	0.56	0.57
Germany	0.67	0.65	0.63	0.59	0.56	0.52	0.51	0.55	0.59	0.66	0.68	0.66	0.65	0.65	0.67	0.68	0.68	0.68	0.71
Greece			0.85	0.83	0.84	0.79	0.74	0.65	0.69	0.74	0.72	0.70	0.71	0.71	0.73	0.79	0.85	0.78	0.73
Indonesia										0.97	0.97	0.96	0.97	0.96	0.97	0.97	0.96	0.97	0.97
Ireland	0.39	0.37	0.35	0.34	0.35	0.38	0.41	0.39	0.40	0.47	0.49	0.48	0.47	0.47	0.48	0.49	0.48	0.42	0.42
Italy	0.85	0.86	0.85	0.85	0.83	0.82	0.83	0.83	0.84	0.85	0.84	0.86	0.87	0.86	0.86	0.86	0.85	0.84	0.83
Japan	0.84	0.84	0.84	0.81	0.80	0.77	0.77	0.78	0.78	0.78	0.77	0.74	0.73	0.72	0.73	0.73	0.73	0.72	0.72
Luxembourg	0.04	0.04	0.05	0.05	0.07	0.07	0.10	0.11	0.14	0.16	0.19	0.16	0.15	0.18	0.23	0.27	0.28	0.27	0.29
Malaysia							0.91	0.92	0.91	0.90	0.90	0.90	0.90	0.88	0.89	0.90	0.90	0.91	0.90
Mexico			0.98	0.97	0.95	0.96	0.96	0.95	0.97	0.97	0.98	0.98	0.98	0.97	0.97	0.96	0.97	0.97	0.97
Netherlands	0.63	0.62	0.61	0.59	0.56	0.55	0.59	0.64	0.63	0.62	0.65	0.64	0.60	0.58	0.59	0.61	0.61	0.59	0.59
Norway	0.93	0.92	0.92	0.92	0.88	0.86	0.83	0.83	0.84	0.82	0.78	0.80	0.77	0.75	0.75	0.77	0.78	0.77	0.75
Panama		0.42	0.43	0.43	0.43	0.41	0.39	0.39	0.40	0.40	0.42	0.42	0.44	0.44	0.47	0.50	0.53	0.53	0.53
Philippines																0.90	0.90	0.90	0.90
Portugal	0.76	0.76	0.74	0.74	0.75	0.76	0.76	0.76	0.75	0.79	0.80	0.82	0.81	0.81	0.83	0.84	0.84	0.83	0.82
Russia															0.80	0.83	0.85	0.86	0.85
South Africa									0.87	0.87	0.87	0.86	0.86	0.84	0.87	0.88	0.88	0.88	0.84
South Korea				0.96	0.96	0.96	0.94	0.94	0.95	0.94	0.95	0.94	0.93	0.92	0.92	0.92	0.93	0.93	0.93
Spain	0.83	0.83	0.83	0.82	0.83	0.83	0.84	0.85	0.86	0.87	0.86	0.86	0.85	0.84	0.84	0.80	0.78	0.75	0.74
Sweden	0.80	0.79	0.75	0.73	0.68	0.66	0.66	0.67	0.67	0.67	0.65	0.66	0.64	0.64	0.66	0.64	0.66	0.71	0.71
Turkey	0.87	0.91	0.91	0.92	0.91	0.90	0.89	0.90	0.93	0.95	0.96	0.96	0.97	0.96	0.96	0.95	0.94	0.92	0.93
United States	0.84	0.82	0.81	0.81	0.79	0.77	0.77	0.77	0.74	0.75	0.79	0.81	0.82	0.82	0.82	0.82	0.83	0.82	0.83

Table 3.9: Annual Equity Home Bias for Small Sample of Countries.

Sample / Time	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
By Country																			
Australia	0.83	0.81	0.83	0.85	0.82	0.82	0.79	0.77	0.80	0.79	0.75	0.75	0.72	0.70	0.69	0.68	0.67	0.64	0.60
Austria	0.39	0.48	0.50	0.52	0.58	0.60	0.62	0.47	0.50	0.49	0.43	0.44	0.41	0.35	0.36	0.42	0.38	0.35	0.31
Belgium	0.55	0.47	0.47	0.55	0.50	0.50	0.44	0.34	0.40	0.43	0.42	0.44	0.42	0.42	0.45	0.38	0.35	0.30	
Brazil	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.98	0.96	0.94	0.96	0.96	0.96	0.96
Canada	0.68	0.79	0.72	0.74	0.74	0.72	0.73	0.68	0.71	0.72	0.70	0.67	0.64	0.61	0.54	0.57	0.53	0.50	
Chile	0.93	0.91	0.89	0.88	0.85	0.79	0.76	0.79	0.75	0.77	0.76	0.75	0.70	0.66	0.63	0.63	0.65	0.63	0.54
France	0.79	0.76	0.72	0.69	0.67	0.66	0.67	0.65	0.65	0.62	0.64	0.61	0.60	0.59	0.60	0.59	0.58	0.58	
Germany	0.67	0.59	0.62	0.59	0.56	0.51	0.53	0.49	0.46	0.48	0.48	0.49	0.51	0.47	0.44	0.43	0.44	0.41	0.33
Greece	0.98	0.96	0.95	0.94	0.93	0.92	0.90	0.81	0.86	0.81	0.69	0.83	0.91	0.84	0.68	0.69	0.76	0.75	0.77
Indonesia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.98
Japan	0.88	0.88	0.89	0.87	0.88	0.86	0.84	0.84	0.79	0.80	0.78	0.78	0.81	0.70	0.71	0.69	0.70	0.67	0.52
Malaysia	0.99	0.99	0.99	0.99	0.99	0.98	0.97	0.94	0.93	0.94	0.93	0.93	0.92	0.90	0.88	0.87	0.87	0.86	0.81
Malta	0.99	0.95	0.90	0.82	0.83	0.79	0.77	0.73	0.73	0.71	0.57	1.28	-0.34	-0.00	-0.03	-0.00	-0.00	0.00	0.01
Mexico			1.00	0.98	0.98	0.98	0.99	0.99	0.98	0.98	0.97	0.96	0.94	0.93	0.92	0.91	0.89	0.89	0.88
Norway	0.56	0.47	0.49	0.52	0.52	0.53	0.50	0.35	0.31	0.35	0.28	0.24	0.22	0.19	0.17	0.20	0.19	0.19	0.16
Philippines	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99
Poland	0.99	0.99	0.99	0.99	0.98	0.96	0.94	0.95	0.95	0.94	0.94	0.94	0.94	0.92	0.83	0.87	0.88	0.86	0.84
Portugal	0.81	0.79	0.80	0.75	0.63	0.56	0.53	0.21	0.43	0.32	0.03	0.63	0.61	0.51	0.50	0.50	0.53	0.48	
Slovenia									0.77	0.70	0.63	0.60	0.59	0.60	0.54	0.51	0.48	0.53	0.53
South Africa	0.83	0.86	0.86	0.90	0.89	0.91	0.91	0.88	0.88	0.86	0.84	0.84	0.84	0.84	0.82	0.85	0.86	0.84	0.83
Spain	0.86	0.87	0.88	0.87	0.86	0.85	0.88	0.89	0.91	0.88	0.89	0.87	0.81	0.77	0.68	0.64	0.59	0.57	0.52
Turkey	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
United States	0.68	0.68	0.65	0.65	0.60	0.57	0.55	0.57	0.55	0.54	0.49	0.48	0.46	0.43	0.40	0.40	0.38	0.38	
By Group																			

Notes:. We do not report the home bias for Luxembourg, Ireland, and Panama.

Table 3.10: Annual Equity Home Bias for Large Sample of Countries.

Sample / Time	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
By Country																			
Australia	0.83	0.81	0.83	0.85	0.83	0.82	0.79	0.77	0.80	0.79	0.75	0.75	0.72	0.70	0.69	0.68	0.67	0.64	0.62
Austria	0.39	0.48	0.50	0.52	0.58	0.60	0.62	0.47	0.50	0.49	0.43	0.44	0.41	0.36	0.36	0.42	0.38	0.35	0.31
Belgium	0.55	0.47	0.47	0.55	0.50	0.50	0.44	0.34	0.40	0.43	0.42	0.44	0.42	0.42	0.45	0.38	0.35	0.30	
Brazil	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.98	0.96	0.94	0.96	0.96	0.96	0.96
Bulgaria	1.07	1.00	1.00	0.99	0.99	0.98	0.97	0.99	0.94	0.90	0.94	0.92							
Canada	0.69	0.79	0.72	0.74	0.75	0.72	0.73	0.68	0.72	0.73	0.70	0.68	0.64	0.61	0.55	0.57	0.54	0.50	
Chile	0.93	0.91	0.89	0.88	0.85	0.79	0.76	0.79	0.75	0.77	0.76	0.75	0.70	0.66	0.63	0.63	0.65	0.63	0.54
China															0.98	0.97	0.96	0.95	0.93
Croatia																			
Denmark	0.62	0.65	0.61	0.62	0.59	0.53	0.56	0.67	0.46	0.48	0.53	0.40							
Estonia	0.98	0.97	0.93	0.88	0.80	0.64	0.59	0.77	0.52	0.44	0.39	0.32							
Finland	0.87	0.80	0.67	0.62	0.57	0.51	0.49	0.74	0.18	0.04	0.38	0.35							
France	0.79	0.77	0.72	0.69	0.68	0.66	0.67	0.65	0.66	0.63	0.64	0.61	0.60	0.59	0.60	0.59	0.58	0.59	
Germany	0.67	0.59	0.62	0.59	0.56	0.51	0.54	0.49	0.47	0.49	0.48	0.50	0.52	0.48	0.45	0.43	0.45	0.41	0.37
Greece	0.98	0.96	0.95	0.94	0.93	0.92	0.90	0.81	0.86	0.81	0.69	0.83	0.91	0.84	0.68	0.69	0.76	0.75	0.77
Hungary		0.97	0.97	0.94	0.91	0.82	0.77	0.66	0.66	0.61	0.64	0.66	0.63	0.53	0.58	0.64	0.66	0.66	0.65
Indonesia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.98
Italy	0.68	0.62	0.56	0.57	0.56	0.51	0.56	0.68	0.48	0.46	0.45	0.35	0.32	0.36					
Japan	0.89	0.88	0.89	0.88	0.88	0.86	0.84	0.85	0.80	0.80	0.78	0.78	0.81	0.71	0.71	0.70	0.71	0.68	0.61
Latvia						0.89	0.85	0.83		0.51	0.25	0.32							
Lithuania										0.72	0.72	0.66							
Malaysia	0.99	0.99	0.99	0.99	0.99	0.98	0.97	0.94	0.93	0.94	0.93	0.93	0.92	0.90	0.88	0.87	0.87	0.86	0.81
Malta	0.99	0.95	0.90	0.82	0.83	0.79	0.77	0.73	0.73	0.71	0.57	1.28	-0.34	-0.00	-0.03	-0.00	-0.00	0.00	0.01
Mexico			1.00	0.98	0.98	0.98	0.99	0.99	0.98	0.98	0.97	0.96	0.94	0.93	0.92	0.91	0.89	0.89	0.88
Netherlands	0.48	0.44	0.33	0.28	0.33	0.36	0.45	0.30	0.30	0.33	0.33	0.30	0.28	0.25	0.21	0.21	0.24		
Norway	0.56	0.47	0.49	0.52	0.52	0.53	0.50	0.35	0.31	0.35	0.28	0.24	0.22	0.19	0.17	0.20	0.19	0.19	0.17
Philippines	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99
Poland	0.99	0.99	0.99	0.99	0.98	0.96	0.94	0.95	0.95	0.94	0.94	0.94	0.94	0.92	0.83	0.87	0.88	0.86	0.84
Portugal	0.81	0.79	0.80	0.75	0.63	0.56	0.53	0.21	0.43	0.32	0.03	0.63	0.61	0.51	0.50	0.50	0.53	0.48	
Romania	0.99	0.99	1.00	1.00	0.99	0.98	0.97	0.95	0.95	0.94	0.92								0.92
Slovenia									0.77	0.70	0.63	0.60	0.59	0.60	0.54	0.51	0.48	0.53	0.53
South Africa	0.83	0.86	0.86	0.90	0.89	0.91	0.91	0.88	0.89	0.86	0.84	0.84	0.84	0.85	0.82	0.85	0.86	0.84	0.84
Spain	0.86	0.87	0.88	0.87	0.86	0.85	0.88	0.89	0.91	0.88	0.89	0.87	0.82	0.77	0.68	0.64	0.59	0.57	0.53
Sweden	0.65	0.63	0.55	0.58	0.57	0.55	0.59	0.66	0.42	0.50	0.58	0.48							
Turkey	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
United Kingdom	0.72	0.72	0.65	0.65	0.60	0.57	0.59	0.67	0.47	0.56	0.61	0.52							
United States	0.75	0.75	0.72	0.71	0.67	0.64	0.63	0.65	0.62	0.62	0.59	0.57	0.53	0.53	0.52	0.52	0.50	0.48	

Notes:. We do not report the home bias for Cyprus, Luxembourg, Ireland, and Panama.

3.8.3 Empirical Facts

US Trends

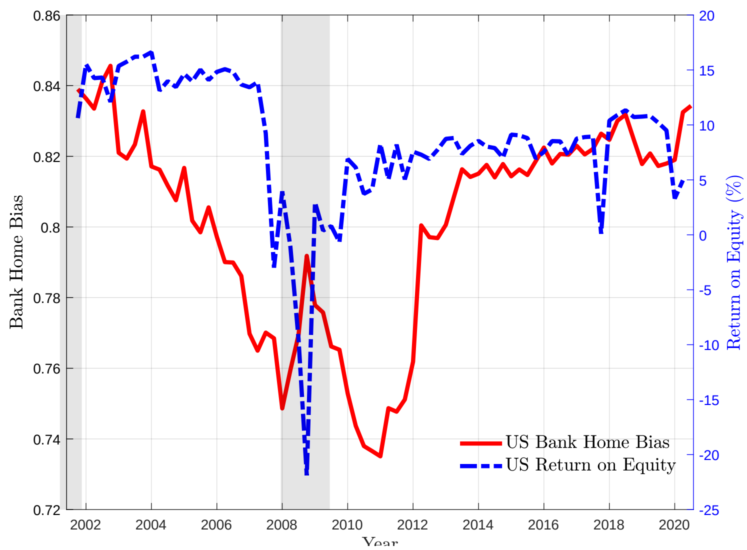

Figure 3.20: US Bank Home Bias and Return on Equity.

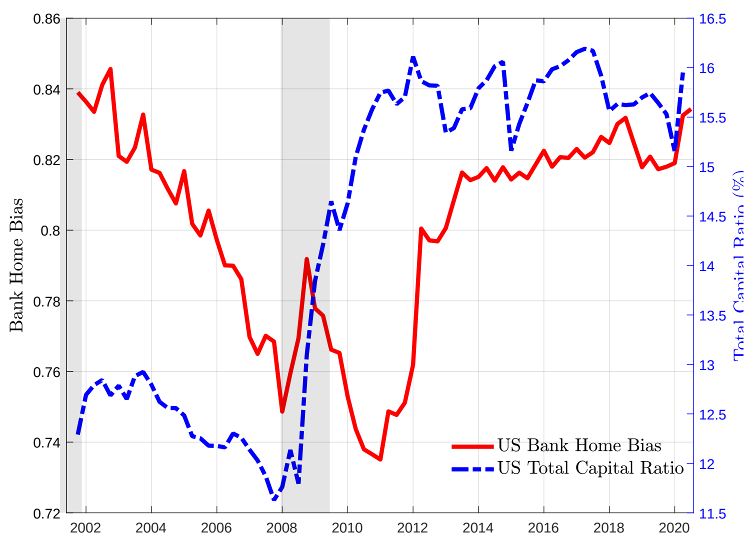

Figure 3.21: US Bank Home Bias and Total Capital Ratio.

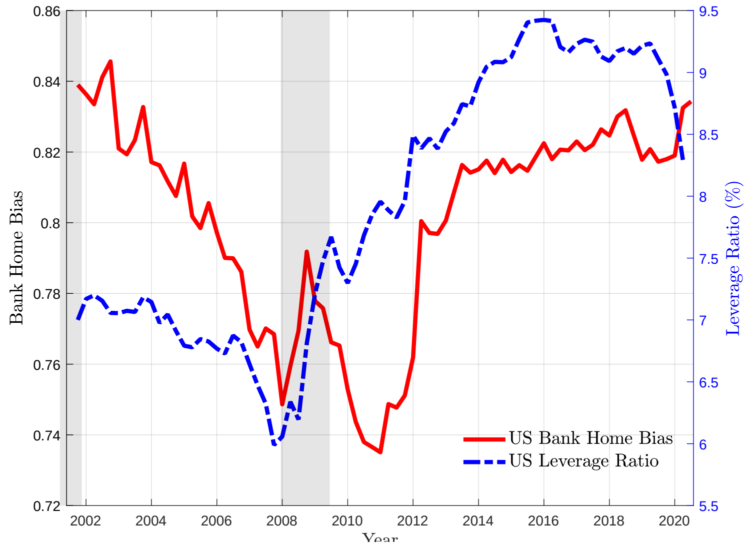

Figure 3.22: US Bank Home Bias and Leverage Ratio.

Sub-group Trends

We classify the countries in our sample to the following sub-categories, such that World ≡ Europe + America + Africa + Asia + Others.

North Eurozone : *Austria, Belgium, Finland, France, Germany, Ireland, Luxembourg, Netherlands.*

South Eurozone : *Cyprus, Greece, Italy, Portugal, Spain.*

North America : *Canada, UnitedStates.*

South America : *Brazil, Bahamas, Chile, Mexico, Panama.*

Africa : *SouthAfrica.*

Asia : *Indonesia, Japan, South Korea, Malaysia, Philippines*

Others : *Australia, Russia, Turkey.*

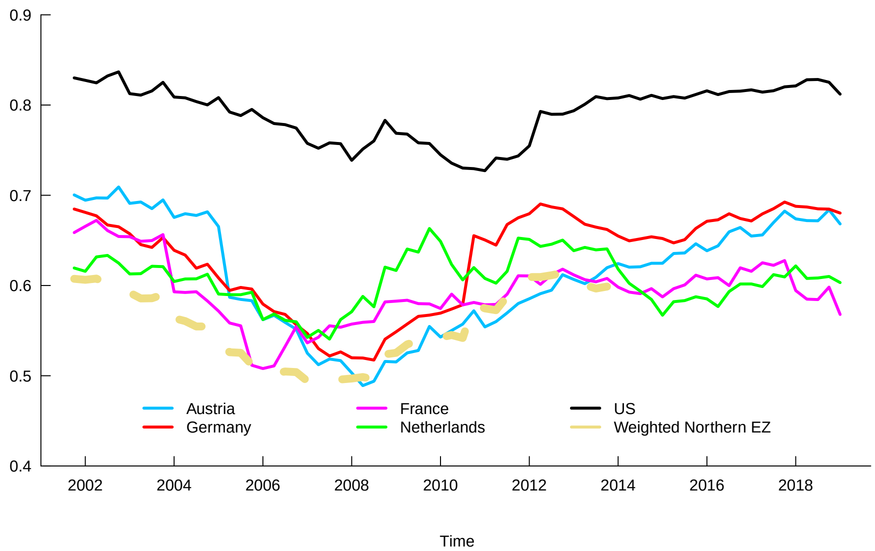

Figure 3.23: Northern European home bias in total bank assets over time.

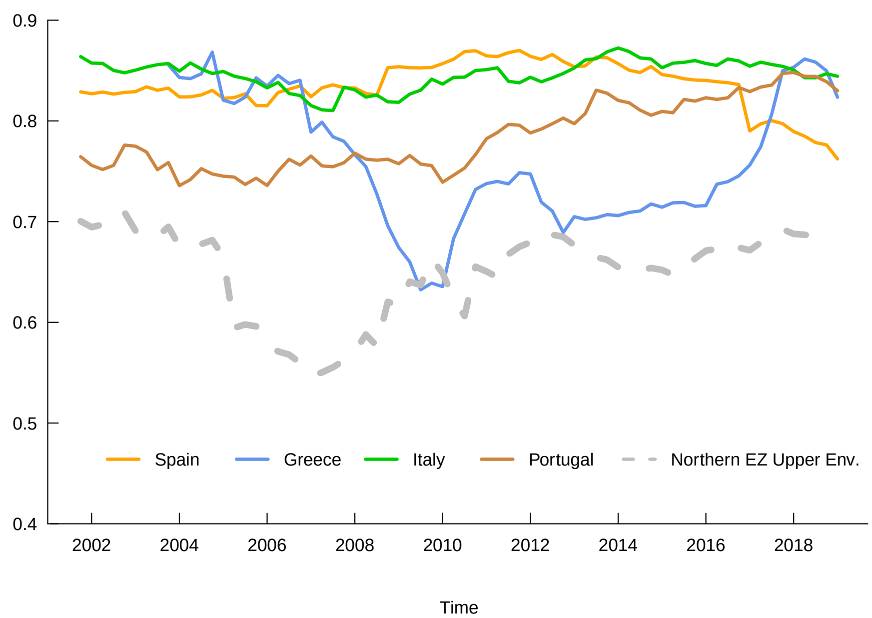

Figure 3.24: Southern European home bias in total bank assets over time.

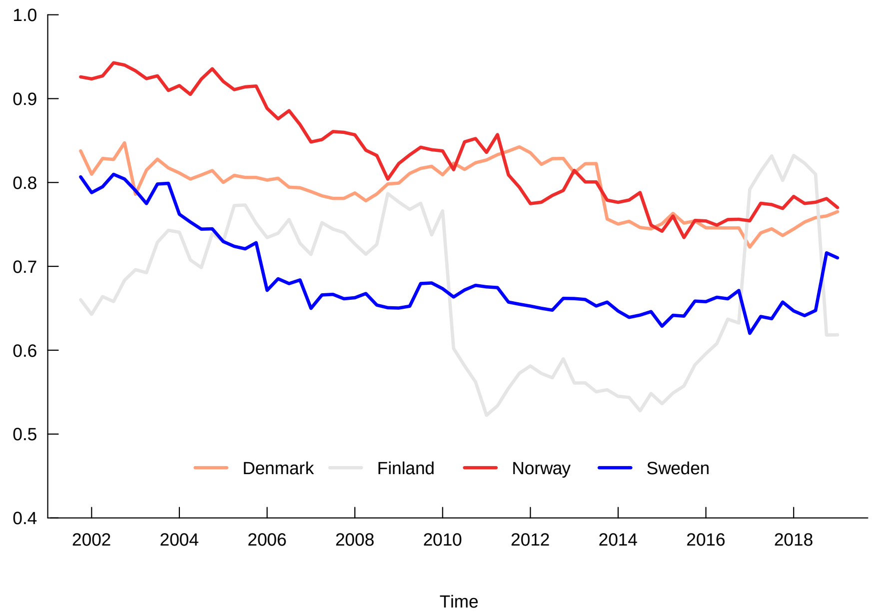

Figure 3.25: Scandinavian home bias in total bank assets over time.

Distribution of Individual Home Bias

To further investigate the home bias against particular sub-groups of countries, let us define the following variables:

$c_{i,j,t} \equiv$ cross-border assets of country i towards country j

$d_{i,t} \equiv$ domestic assets of country i

$f_{i,t} \equiv$ foreign banking assets to country i

$w_t \equiv$ worldwide banking assets

Home bias of country i at time t is given by

$$hb_{i,t} \equiv 1 - \frac{\frac{c_{i,t}}{c_{i,t}+d_{i,t}}}{\frac{f_{i,t}}{w_t}} = 1 - \frac{\frac{c_{i,t}}{c_{i,t}+d_{i,t}} \sum_j \frac{c_{i,j,t}}{c_{i,t}}}{\frac{f_{i,t}}{w_t}} .$$

Conditional on domestic lending $d_{i,t}$ the distribution of home bias is characterized by $\chi_{i,j,t} \equiv \sum_j \frac{c_{i,j,t}}{c_{i,t}}$. We perform this analysis for the four countries, and the results are shown in Figure 3.26.

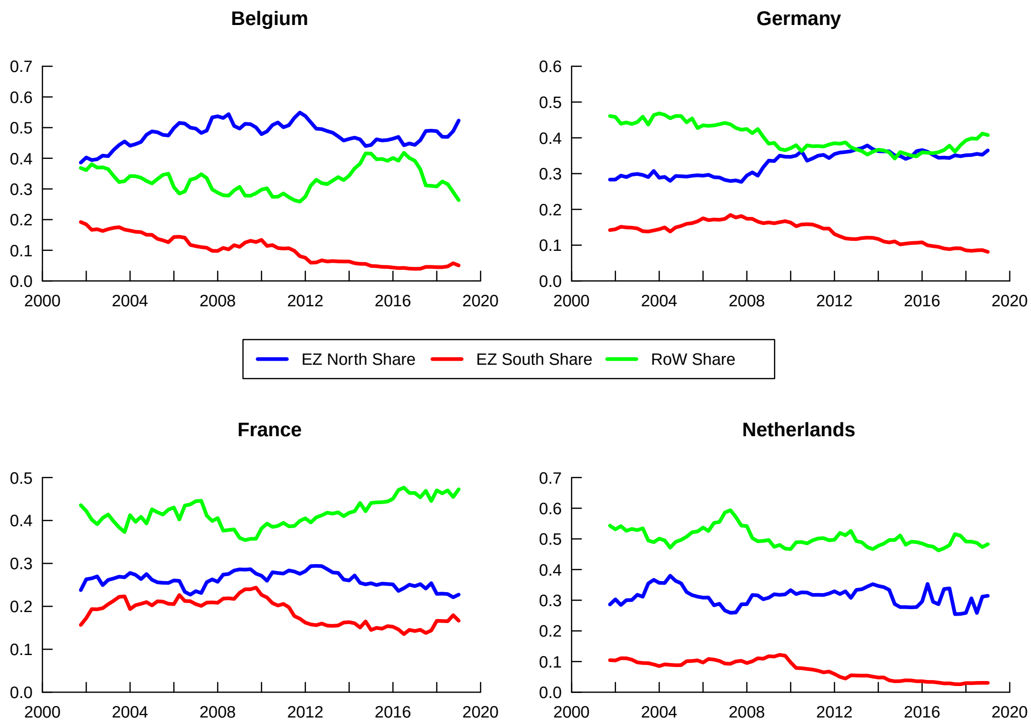

Figure 3.26: Home Bias distribution along the business cycle.

Chapter 4

Uncertainty Shock(s)

Li Yu and Hussein Bidawi[1]

4.1 Introduction

Uncertainty, broadly defined as the second-order moment that reflects the accuracy of the prediction of future events, has become an object of interest in recent economic studies and policy-making circles, notably after the Great Recession and the COVID-19 pandemic era. Nevertheless, pinpointing the effect of uncertainty through identifying exogenous uncertainty shocks is notoriously tricky. They are often subject to two significant challenges: the difficulty in directly measuring the second-order moments and the forward-looking nature of uncertainty. Literature has proposed various approaches to quantify uncertainty, including survey-based, text-based (Baker et al., 2016; Ahir et al., 2018; Husted et al., 2020), and volatility or dispersion-based measurements.

One group of frequently used measurements is the volatility of financial assets, which addresses the aforementioned challenges. First, volatility data is sufficiently rich in terms of frequency and categories. Second, due to the active trading of the derivatives of these assets, the implied volatility computed using forward-looking derivative prices contains considerable information on the forward-looking component. Recent literature exploits this advantage of financial asset volatilities to achieve better identification results of uncertainty shocks. Among these studies, Berger et al. (2020) propose an identification scheme in structure vector auto-

[1]We are deeply indebted to our advisor Patrick Fève for invaluable and continuous support. We would like to thank the participants in the TSE macro workshop for useful feedback and comments. All errors are, of course, our own.

regression (SVAR) model employing both realized and implied volatilities of the equity. The methods can separately identify the uncertainty shock that affects the future and a shock to realized volatility, of which only the former is the, strictly speaking, uncertainty shock.

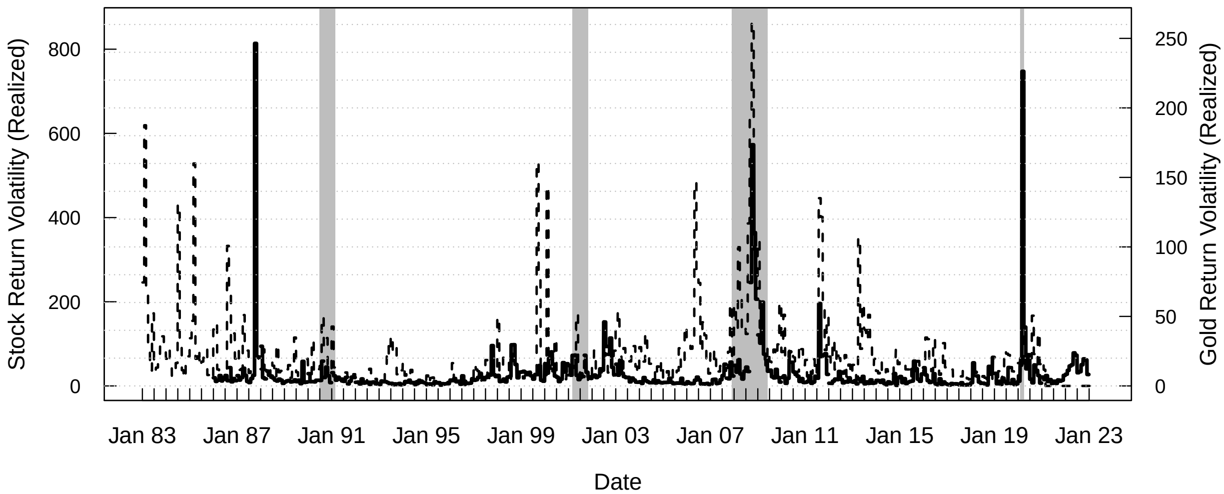

Figure 4.1: Asset Return Volatility: Stock vs. Gold.

Notes: The solid line displays the realized volatility of the stock returns in the US, and the dashed line the realized volatility of gold return volatility. Shaded regions denote the recession period.

This paper builds on the recent developments of uncertainty shock identification and takes it one step further by asking the following questions: Do the volatilities of different financial assets have the same informational content regarding the uncertainty about the future of the economy? If not, what factors contribute to the heterogeneity in their economic impacts, and what are the implications for understanding the link between macro and financial uncertainty?

Examining uncertainty shocks across multiple assets within a unified framework is of great importance. Recent research on uncertainty shock identification often uses equity volatilities. However, with a single asset, it is impossible to determine whether the uncertainty shock identified is driven mainly by the information they contain regarding economic fundamentals or asset-specific characteristics. For instance, as shown in Figure 4.1, the volatilities of stock and gold returns exhibit correlated patterns but differ in scale and variations, which reflects that significant asset-specific driving factors exist for volatility. In addition, Figure 4.22 and Figure 4.23 in the Appendix 4.6.2 compare the volatility of stock return to that of oil and foreign exchange, which also differ significantly. While stock and oil price volatilities both reflect the degree to which the economy will undergo volatile periods, the oil price has a more direct impact on manufacturing industries, and stock captures mainly the outlooks of large firms. Similarly, foreign exchange volatility presumably responds to the uncertainty of the expectations of industries that rely heavily on import goods or foreign upstream firms. The informational content of their volatilities can thus be vastly different and worth comparison.

Although the existing literature has explored uncertainty shocks using various assets, the results are often vastly different and incomparable due to different identification schemes. Cross-checking the responses to different uncertainty shocks also sheds light on the channels through which uncertainty shock is transmitted through the economic system. This approach is only possible if the shocks are identified using the same framework. The differences revealed in asset volatilities expose these channels and emphasize the importance of studying uncertainty shocks across multiple assets within a uniform framework.

Our contribution is thus two-fold. First, we provide novel evidence on the heterogeneity in responses of real economic variables to uncertainty shocks identified using different assets. We show that in the period after the Great Recession, uncertainty shocks identified using gold volatilities induced a substantially larger and more persistent real effect than stock volatilities. In addition, by incorporating additional indices on non-fundamental variables, we find that uncertainty shock can have an impact on the real economy by affecting the sentiment, such as consumer sentiment and investor risk appetite. Second, we sketch a simple theoretical framework of consumption-based asset pricing with noisy information to illustrate the mechanism. We show that fundamental uncertainty, asset-specific uncertainty, and non-fundamental factors such as prediction errors and risk-aversion variations can jointly contribute to asset volatility variations, which can account for the heterogeneity in the uncertainty shocks identified using different asset volatilities.

We start by documenting the statistical properties and stylized facts of first and second-order moments of several asset prices: stocks, gold, oil, and the euro-dollar exchange rate. A systematic exploration of the data would start by looking at the behavior of the correlation matrix between returns, realized volatilities, and implied volatilities across the main assets. Our main finding is that second-order moments, in specific implied volatility, are systematically more correlated across assets than first moments. This contrasts with the behavior of returns that are less correlated across assets. We interpret this as evidence that second-order moments are more likely to have common drivers: aggregate uncertainty, investor sentiment, monetary policy, and risk appetite, among others. Furthermore, the higher correlation of implied volatility highlights that agents' expectations about the future are more sensitive to common factors potentially related to them than to idiosyncratic and asset-specific shocks. Lastly, we generalize the finding in Berger et al. (2020) of the high correlation between realized and implied volatility of stock prices to other asset classes such as oil, gold, and the Euro-Dollar exchange rate. Moreover, returns are often not correlated to either volatility, implied, or realized.

Based on these facts, our analysis of uncertainty shock starts by applying current identification schemes of uncertainty shock in the existing literature to different types of volatilities. To start with, we study the effects of using only one uncertainty measure on economic activity in an otherwise standard structural VAR. Our measurement of choice is the Financial Uncertainty Index, a measure of uncertainty based on the volatility of forecast errors developed by Jurado et al. (2015). This index reflects the information from the financial market and thus offers a convenient baseline for comparing uncertainty shock driven by asset volatilities. By ordering it first in a Cholesky scheme, otherwise known as short-run restrictions identification, in an SVAR model, we find that economic policy uncertainty shocks have strong and short-lived effects on real economic activity, which align with previous studies in the literature (in particular, the seminal work of Bloom (2009)). Additionally, the shock generates a decrease in indices that we label as indicators of sentiment, including both sentiment of investors, as captured by an increase in risk aversion measured by the Excess Bond Premium Gilchrist and Zakrajšek (2012), and the sentiments of consumers decrease in sentiment (a rise in pessimism), as measured by the Index of Consumer Sentiment and Inflation Expectation developed by the University of Michigan. This result points to a potentially neglected channel of transmission of uncertainty shocks: uncertainty can affect real economic activities by changing the sentiments of both financial market participators and regular households; that is, higher uncertainty might weigh in on people's minds and negatively bias their perception of the current economic condition. It is essential to answer: Do consumers and investors react to uncertainty by considering it as second-order moments or waves of optimism and pessimism (the animal spirits of Keynes)?

Furthermore, Berger et al. (2020) further argues that one must employ both *realized* and *implied* volatility measure and impose restrictions to separate uncertainty news and impose further restrictions to correctly identify uncertainty shocks, which by definition are about the future, using insights from the news shocks literature. Contemporaneous variations in volatility are excluded, as they do not pertain to the future. We investigate the validity of their approach and find that the findings vary when we change the sample period and asset classes. Uncertainty news shocks cause a persistent contraction in output and employment in our data from 2008 to 2019, which contradicts the findings of Berger et al. (2020). Interestingly, for stock volatility, the uncertainty news shock is accompanied by an increase in the policy rate. In the meantime, uncertainty shocks generated by different financial assets also trigger changes in sentiment-related variables, although the responses vary across assets and sentiment indices. We find that stock uncertainty shocks generate large responses from investors on impact, measured by Excess Bond Premium, whereas gold uncertainty shocks have a more substantial and persistent effect on consumer sentiment, captured by the Consumer Sentiment Index.

The results point to the mixing of the aggregate and asset-specific uncertainty and the difficulty distinguishing between uncertainty shock from contamination of other factors. Since a shock to the accuracy of the agent's expectations could come from an increase in the objective uncertainty of the outcome of interest (an increase in the standard deviation of the GDP of economic or financial fundamentals) or an increase in the perceived or subjective uncertainty of the fundamental by the agent, an exogenous change to agent's risk aversion or risk tolerance is also a second order moment shock that would affect volatility today and expectations about future volatility. Moreover, a generalized sentiment of optimism or pessimism would generate both a change in returns and the accuracy of expectations about the future, which suggests potential contamination between second-order uncertainty and first-order expectation adjustments that complicate the life of the econometrician when identifying these different shocks. Furthermore, big crises often come with large swings in many objects of interest. As witnessed in the recent COVID-19 pandemic (and similarly in the Global Financial Crisis), these big shocks result in significant increases in volatility, realized and implied sentiment (pessimism), and risk aversion. The link between such shocks intimately linked to uncertainty, real economic activity, and the role of expectations about the future becomes a tricky question to answer empirically.

As a first step to tackle this problem, we sketch a clear and concise analytical framework of asset pricing under noisy information. The framework reveals that asset-volatilities are a reflection of both asset-specific uncertainty and the fundamental uncertainty of the economy. Additionally, given that the agents can make prediction errors when forming their expectations, the volatilities of assets generated by the model contain the stochastic variances of the non-fundamental factors, which speaks to the sentiment-related variables such as consumer sentiments and investors' risk appetite in the empirical findings. Utilizing this framework, we can delve deeper into the mechanism behind asset volatilities and their impact on economic outcomes. It allows us to gain valuable insights into the relationship between market volatility, investor behavior, and economic conditions. Through this lens, we can identify potential connections between second-order moments, first-order expectation changes, and behavioral factors, and bridge the gap between empirical and theoretical studies of uncertainty and sentiment. As a next step, we plan to simulate the model and pin down the parameters that govern the composition of asset volatilities by comparing the simulation results to our empirical findings.

Literature Our paper mainly relates to three fields of literature: The impact of uncertainty on the real economy, SVAR identification of uncertainty shocks, and the relationship between uncertainty and volatility.

To start with, our work adds to the burgeoning literature on quantifying the impact of uncertainty shocks on macroeconomics. The problem includes two sub-tasks. First, one needs proper measurements or proxy variables that can capture, to some extent, the second-order moment that is uncertainty[2]. Second, making causal statements on the impact of uncertainty on the economy requires credible identification of exogenous uncertainty shocks. While most works confirm that uncertainty shocks have a negative effect on output. (Bloom (2009), Basu and Bundick (2017), Bloom et al. (2018)).[3]

Second, our work contributes to the identification of uncertainty shock under the SVAR framework. SVAR models with different identification approaches have been proposed to identify exogenous uncertainty shocks, including short-run identification (Bloom (2009), Jurado et al. (2015)), sign restriction (Caldara et al. (2016)), proxy VAR (Gazzani and Vicondoa (2020)), the methodology elaborated to identify news shock (Berger et al. (2020)).[4] While others, notably, Berger et al. (2020) argue that a distinction needs to be made between current volatility, which measures how large the shocks that just occurred, from uncertainty, which is the expected magnitude of future shocks by agents. When doing so, they find that shocks to future uncertainty that are orthogonal to realize volatility do not cause a contraction in output. While we follow the identification strategy of BDG and expand it to other assets, we find opposite results: shocks to uncertainty cause a persistent dip in real economic activity

[2] For more introduction on the measurements of uncertainty, see Appendix 4.6.1 for a brief review.

[3] See also Leduc and Liu (2016), Fernández-Villaverde et al. (2015), Born and Pfeifer (2014), Biljanovska et al. (2021).

[4] More recent papers use statistic driven identification methods instead for example by departing from Gaussianity: Lanne et al. (2017) use MLE and student-t distribution, Alessandri et al. (2020)use Independent Component Analysis, Lanne and Luoto (2021)use GMM and Co-kurtosis. Others use high-frequency data and heteroskedasticity such as Gazzani and Vicondoa (2020) or sign restriction identification on information shock from monetary policy announcements (Jarociński and Karadi (2020)).

and employment. This result is in line with the earlier studies.

Lastly, our paper contributes to the literature on the relationship between asset volatility, macro uncertainty, and higher-order beliefs. Following Hassan and Mertens (2017), Miao et al. (2021) provides a theoretical framework of production-based asset pricing with endogenous SDFs and prediction error, showing that with the presence of common forecast error, stock volatility increases sharply with TFP volatility. Our results provide empirical evidence on the link between volatilities and non-fundamental factors, proxied by sentiment or risk-taking appetite.

Layout The rest of the paper is structured as follows. Section 4.2 introduces the current identification schemes of uncertainty shocks, tests the method using different asset classes, and proposes methods to improve the identification schemes. Section 4.3 sketches a theoretical framework to rationalize the empirical findings. Finally, Section 4.4 concludes.

4.2 Empirical Analysis

4.2.1 Framework

To elucidate the concepts, we start with the basic framework of asset pricing

$$P_t = \frac{\mathbb{E}_t\left[\sum_{s\geq t} M_s D_s\right] U_{t+1}}{M_t}$$

where M_{t+1} is the pricing kernel and D_s the dividend stream[5]. Using the consumption-based asset pricing model, we express the pricing kernel as $M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma_t}$, where C_t are the consumption. U_t denotes the stochastic variable that drives aggregate fluctuations[6], and γ_t is the risk-aversion.

From this general framework, we can already see that the volatility of asset prices, or returns, can be attributed to several stochastic components: Dividend process D_s, pricing kernel

[5] Admittedly, assets such as gold, oil, or foreign exchange do not pay dividends. Therefore, the dividend here is to be understood as the benefits of holding these assets, as opposed to a strict pecuniary dividend. For instance, the benefits of holding oil and foreign exchange can be future profits from production or transaction using these assets. The *dividend* obtained from holding gold could be the benefit of hedging against inflation. Therefore, developments in specific markets, such as oil production cuts, could affect the benefits of holding that particular asset.

[6] Candidates for the stochastic variable that drives aggregate fluctuation, U_t, include the rare disaster that drives the consumption growth away from its normal time growth rates (Gabaix, 2008, 2012), and the error agents makes when forming their expectations (Hassan and Mertens, 2017). Effectively, the term can denote anything that is not fundamental but affects consumption decisions or utility flows.

or stochastic discount factor M_t determined by aggregate fundamentals, and non-fundamental factors, such as common prediction error, captured by U_t, and time-varying risk-aversion (or risk-appetite), captured by γ_t. For simplicity, we refer to these non-fundamental factors broadly as sentiment-related variables, or *sentiments*. Consequently, the impacts of uncertainty shocks on the real economy naturally differ when we use different asset classes for identification, as the asset volatilities reflect different degrees of variations in these three components. We empirically examine the differences in the uncertainty shocks identified from these perspectives in the following sections.

4.2.2 Data and Variable

Uncertainty

This section introduces the uncertainty measurements used in the empirical analysis[7].

Asset Volatilities The key measurements of interest are the realized and implied volatilities of the financial assets, which are the key to identifying the uncertainty shock. Define s_t as the log of an asset's price, for example, a stock market index. The one-period log return r_t is defined as follows:

$$r_t \equiv s_t - s_{t-1} \tag{4.2.1}$$

Following Berger et al. (2020), we define the realized volatility RV_t of an asset class as the sum of squares of daily returns over a rolling window of size T that ends at day t[8]:

$$RV_t \equiv \sum_{i=t-T}^{t} r_i^2 \tag{4.2.2}$$

The implied volatility, on the contrary, is a *forward-looking* index in the sense that it reflects the uncertainty about future returns, measured as the conditional variance $Var_t[s_{t+T}]$. If periods are sufficiently short and returns are unpredictable such that $E_t r_{t+1} \approx 0$, the implied volatility can be defined as the expectation of future squared daily returns over a window of size T starting at day t:

$$IV_t = Var_t[s_{t+T}] \approx E_t \left[\sum_{j=t}^{t+T} r_j^2 \right] \tag{4.2.3}$$

[7] For a more detailed description of different approaches to uncertainty measurements, see Appendix 4.6.1.

[8] In the benchmark setup, we set the window size to a calendar month, and include trading days of this window for the calculation of daily returns and realized volatility.

Thus, implied volatility of an asset class is closely linked to realized volatility but contains different information, as the former is the expected value from the latter:

$$IV_t \approx E_t \left[\sum_{j=t}^{t+T} RV_j \right] \tag{4.2.4}$$

The above expression indicates that the conditional variance as an asset price on some future date is the expected total variance of returns over that period. As such, an uncertainty shock alters expected future volatility, which differs from a shock to current squared returns. Uncertainty is a concept that relates to the future and not realized and current volatility. Realized volatility might correlate with the expectation of future volatility, as stressed by Berger et al. (2020). However, they are not the same object, which justifies why they try to identify shocks to implied that are orthogonal to shocks to realized volatility.

Since our goal is to analyze how different financial assets' volatilities differ regarding their information content of uncertainty, we select four asset classes: Stock, gold, oil, and Eurodollar foreign exchange. The realized volatilities are computed directly from the asset prices, and their implied volatilities are readily available from the Chicago Board Options Exchange[9]. The details of the variables used are summarised in Table 4.3. As an overview of the general feature of these volatilities, we start by examining their patterns across time. Specifically, we document the statistical properties of the different asset classes by computing the realized volatility levels of each asset class over three sub-samples: pre-Global Financial Crisis (GFC), post-GFC, and during the COVID-19 pandemic, as shown in Table 4.1. We then compare it to the average implied volatility over the same sub-sample for which the data is available, as shown in Table 4.2. Additional descriptive statistics of the financial asset volatilities can be found in Appendix 4.6.2.

We highlight three key features of the observations. First, realized volatilities show some time variation: realized volatilities of stocks and gold substantially increased pre and post-2008 Global Financial Crisis, with realized volatility of stocks and oil prices overshooting during the COVID-19 pandemic by multiples of their pre-pandemic levels. Second, implied volatilities of the different asset classes do not vary substantially over time and are remarkably stable across the different sub-samples. The fact that one is time-varying while the other is not confirms the hypothesis that implied and realized volatilities have different drivers, consistent with implied volatility having more forward-looking information at the time of the observa-

[9]See Appendix 4.6.1 for more description

	Pre-GFC	Post-GFC	COVID
	1983-2008	2008-2020	2020-2021
Stock	24.06	31.96	100.31
Gold	19.21	26.36	26.24
Euro-Dollar	6.81	7.43	4.02
Oil	127.92	116.25	818.20

Table 4.1: Volatility Levels (Realized).

Notes: The realized volatilities of each of our asset classes (Stocks, Gold, Euro-Dollar exchange rate and oil) over three-sub-samples: pre Global Financial Crisis (GFC), post GFC and during the COVID-19 pandemic

	Pre-GFC	Post-GFC	COVID
	1983-2008	2008-2020	2020-2021
Stock	19.03	19.37	20.21
Gold		18.93	19.17
Euro-Dollar		10.46	10.22
Oil		36.33	38.55

Table 4.2: Volatility Levels (Implied).

Notes: The average implied volatilities of each of our asset classes (Stocks, Gold, Euro-Dollar exchange rate and oil) over three-sub-samples: pre Global Financial Crisis (GFC), post GFC and during the COVID-19 pandemic.

tion. Lastly, while realized and implied volatilities are generally highly correlated within asset classes, implied volatility has a much higher correlation across assets than realized volatility, as shown in Table 4.4 to 4.9 in Appendix 4.6.2. The difference indicates implied volatilities share more comment components, whereas realized volatility is more subject to asset-specific factors.

We perform principal component analysis to pinpoint the correlation across asset volatilities further. The results are summarized in Table 4.10. The table clearly shows that both implied and realized the four different assets have common components. 63% of the total variance of realized volatility could be explained by one component, while 75% of the total variance of implied volatility is explained by one component. The fact that implied volatility, our measure of uncertainty because of its forward-looking nature, has a larger common component than realized volatility again indicates that ex-ante expectations of investors about future prices of different asset classes are more driven by common factors.

Alternative Measurements As a comparison to asset volatility, we use alternative measurements for uncertainty developed by Jurado et al. (2015). The paper proposes econometric methods that measure uncertainty using a variety of observations on macro and financial volatilities. The approach is to construct individual uncertainties based on the conditional volatility of forecast error and then construct general uncertainty indicators using the weighted average of individual uncertainty indices. Therefore, the measurement approach of Jurado et al. (2015) has similar informational content to the concept of implied volatilities. Based on this approach, the paper provides three sets of uncertainty indicators: macro, financial, and real. Since our analysis focus on uncertainty associated with asset volatilities, we use the financial uncertainty index as the main indicator. Ludvigson et al. (2021).

Sentiment

As shown in the analytical framework, several non-fundamental factors, including common prediction errors and time-varying risk-aversion, can contribute to the volatilities. Therefore, we use the following sets of variables to capture these factors, which we broadly label as sentiment-related variables.

Consumer sentiment Following the common practice of the literature, we start with the *Index of Consumer Sentiment (ICS)*. [10] The ICS is obtained from a survey of consumers. The index is an economic indicator that measures the subjective optimism of consumers about their own finances and the state of the economy more generally. A higher value of the index indicates that consumers are feeling more optimistic. In addition, we also use the *Inflation Expectation (MICH)* as a more direct measurement that captures the first-order expectation variations of the households.

Investor sentiment We use two indicators to capture bond and equity market sentiment, respectively. For the bond market, we use *Excess Bond Premium (EBP).* a measure of credit spreads the net of an estimate of default risk. The measure is frequently used to gauge investor sentiment or risk appetite in the corporate bond market.[11] The methodology is derived

[10] the University of Michigan, University of Michigan: Consumer Sentiment (UMCSENT), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UMCSENT, August 20, 2022.

[11] For a full description, the reader is referred to Gilchrist et al. (2016): "Gilchrist and Zakrajšek (2012) (GZ hereafter) introduce a corporate bond credit spread with a high information content for economic activity that is built from the bottom up, using secondary market prices of senior unsecured bonds issued by a large representative sample of U.S. non-financial firms. To avoid duration mismatch issues, which can contaminate the information content of credit-risk indicators, yield spreads for each underlying corporate security are derived from a synthetic risk-free security that exactly mimics the cash flows of that bond."

in Gilchrist and Zakrajšek (2012), and the data is obtained from the website of the Federal Reserve.[12] For the equity market, we use *Cboe SKEW Index (SKEW)*, which estimates the skewness of S&P 500 returns at the end of a 30-day horizon. The index is calculated based on the implied volatility of out-of-the-money S&P 500 options and is designed to measure the perceived tail risk of extreme negative market events. The index is constructed so that a higher value indicates an increased perception of tail risk, i.e., the perceived risk of extreme negative events in the market, which is also interpreted as increased risk aversion (or less risk appetite) among investors.

Real Variables

To measure the responses of the real economy, we use the following variables: Output, unemployment, inflation, and monetary policy rates. Detailed descriptions of the variables can be found in Table 4.12 in Appendix 4.6.3.

4.2.3 Empirical Specification

In this section, we use two identification schemes in the SVAR models for the empirical approach, which we refer to as the benchmark approach and the approach in Berger et al. (2020).

Vector Auto-Regression Model

In order to identify uncertainty shocks and estimate their effects on macroeconomic outcomes, we estimate VAR models of the following form

$$\begin{aligned} y_t &= A_0 + \mathbf{A}_1 y_{t-1} + \cdots + \mathbf{A}_p y_{t-p} + u_t \qquad t = 1, \cdots, T \\ y_t &= A_0 + \mathbf{A}(\mathbf{L}) y_t + u_t \end{aligned} \tag{4.2.5}$$

where y_t is an $k \times 1$ vector of endogenous variables to be specified in the next sections, A_0 is a vector of constants, $\mathbf{A}_i$ are $k \times k$ coefficient matrices at lag i, and u_t are reduced-form errors. Alternatively, we can rewrite the model using the lag operator L and the matrix of lag polynomials, $\mathbf{A}(\mathbf{L})$. Under the usual invertibitlity assumptions, we obtain the moving average

[12]We obtained the latest available data as a comma-separated values (CSV) file at the permanent URL https://www.federalreserve.gov/econres/notes/feds-notes/ebp_csv.

(MA) representation of Equation 4.2.5 in Equation 4.2.6

$$\begin{aligned} y_t =& (I - \mathbf{A}(\mathbf{1}))^{-1} A_0 + \mathbf{B}(\mathbf{L}) u_t \\ \text{where} \quad \mathbf{B}(\mathbf{L}) =& \sum_{j=0}^{\infty} \mathbf{B}_j L^j = (I - \mathbf{A}(\mathbf{L}))^{-1} \end{aligned} \tag{4.2.6}$$

The model can be estimated by standard ordinary least squares (OLS). To identify the structural shock, however, we need to pin down further the relationship between reduced-form innovations and structural shocks. Define ϵ_t as the vector of the orthogonal structural shocks with unit variances. We assume that the relationship between the structural shock and the reduced-form innovations is given by $u_t = \mathcal{S}\epsilon_t$. Therefore, to recover the structural shock from the reduced-form error, we need additional assumptions to pin down one or several columns of matrix $\mathcal{S}$ that correspond to the shock that we are interested in, which, in our case, is the uncertainty shock.

The endogenous variable, y_t consists of three components in the following order: Uncertainty component, macro component, and sentiment component. For the macro component, we use two sets of specifications. The first one is the standard specification, i.e., $y_t^{\text{macro}} = \{\text{output}, \text{inflation}, \text{monetary policy}\}$. In the second specification, we define the macro component to be the same as the specification of Berger et al. (2020), i.e., $y_t^{\text{macro}} = \{\text{monetary policy}, \text{unemployment}, \text{output}\}$, as a comparison. Sentiment components include the consumer, bond investor, and stock market investor sentiment described in the previous section. The uncertainty component includes the variables used for the identification of uncertainty shock. The following two sections present two identification methods in the literature.

Benchmark Identification

In the benchmark setup, we use one variable as the single measure of uncertainty used in the model. Thus, in this exercise, the vector y_t includes three standard endogenous variables: output, inflation, monetary policy rate, and one uncertainty index.

We identify uncertainty shocks by imposing short-run restrictions on the system of endogenous variables of the VAR. The critical assumption we impose is that the innovation in the uncertainty index is *exogenous* to the system and affects all the other endogenous variables contemporaneously. In contrast, the innovations to the other variables do not impact the contemporaneous uncertainty index. Under this assumption, identifying exogenous uncertainty shock is equivalent to obtaining the first column of the matrix $\mathcal{S}$, and this can be easily achieved by performing Cholesky decomposition on the variance-covariance matrix Ω of the estimated reduced form errors u_t. This yields a triangular matrix S and the first column thus pins down the structural shocks ϵ_t:

$$\Omega = \mathcal{S}' \times \mathcal{S} \tag{4.2.7}$$

The impulse response function (IRF) of the endogenous variables to the uncertainty shock identified is thus given by

$$\frac{\partial \mathbb{E}[y_{t+j}|\epsilon_t^u, y_{t-1}]}{\partial \epsilon_t^u} = \mathbf{B}_j \mathcal{S}(:,1) \tag{4.2.8}$$

where ϵ_t^u denotes the period t innovation to the uncertainty index, $\mathcal{S}(:,1)$ denotes the first column of $\mathcal{S}$, and $\mathbf{B}_j$ is the MA representation coefficients.

The benchmark approach identifies the uncertainty shock using one single measure of uncertainty. However, as discussed in the introduction, this approach falls short in separating the uncertainty surprises in the current period from that about future events. The latter is believed to be the *true* uncertainty, while the former merely reflects the volatility or dispersion that has already been observed.

BDG Identification

Since uncertainty is, strictly speaking, about the future, the shock itself should be an exogenous change to beliefs about future events, which is essentially a news shock. Studies on the TFP news shock (Barsky and Sims, 2011; Kurmann and Sims, 2021) show that news shocks can be identified by using forward-looking information variables to generate shocks that are orthogonal to the innovation in current period variables. Therefore, to correctly identify uncertainty shock as a news shock, Berger et al. (2020) propose to utilize two types of asset volatilities that are closely related but contain different amounts of forward-looking information, i.e., realized and implied volatilities. Such a pair of variables allow for the separation of a shock to future and current uncertainty[13].

Following these practices of news shock identification, Berger et al. (2020) includes in the vector y_t realized stock volatility, implied stock volatility, and economic variables, proposes the following identification method for uncertainty shock in three steps.

S1. Impose short-run identification to obtain $\mathcal{S}$ using Cholesky decomposition.

[13] Strictly speaking, only the first shock ought to be classified as a true uncertainty shock. We follow the terminology in Berger et al. (2020) and refer to the first shock as uncertainty news shock and the second as realized volatility (RV) shock

S2. Multiply the Cholesky matrix $\mathcal{S}$ by the sum of the first rows of the MA coefficient matrices $\mathcal{B}_j$ up to lag n and a selection vector e_1 with one in the first place and zeros elsewhere. Denote the resulting vector as γ, i.e., $\gamma = \left(e_1 \sum_{j=1}^{n} \mathbf{B}_j\right) \mathcal{S}\varepsilon_t$.

S3. Setting the first entry of the vector γ to zero and then normalizing the vector yields a vector γ^*, which pins down the uncertainty news shock.

The result of this identification scheme is two-fold. First, the model identifies a surprise shock to realized volatility, pinned down by the first column of the Cholesky matrix $\mathcal{S}$. Since realized volatility is ordered at first, this shock has a contemporaneous impact on implied volatility, and the other variables in the VAR system[14]. Second, following Steps 2 and 3, the model constructs the key shock of interest, referred to as *uncertainty news shock*, as a linear combination of shocks. By definition, this linear combination of shocks can account for the expected sum of the n-step residual innovation in expectations of future volatility, denoted as $E_t \sum_{j=1}^{n} RV_{t+j} - E_{t-1} \sum_{j=1}^{n} RV_{t+j}$. In the meantime, the shock is designed to be *orthogonal* to the innovation to the realized volatility, $RV_t - E_{t-1}RV_t$[15]. As a result, this specification allows realized volatility to impact uncertainty in the future; that is, the model allows for certain degrees of GARCH effect.[16]

The IRF of the shock constructed is thus defined as:

$$\frac{\partial \mathbb{E}[y_{t+j}|\epsilon_t^{nu}, RV_t, y_{t-1}]}{\partial \epsilon_t^{nu}} = \mathbf{B}_j \mathcal{S}\gamma^* \tag{4.2.9}$$

where ϵ_t^{nu} is the uncertainty news shock constructed, which is orthogonal to current period innovations on the uncertainty indicator, in this case, the realized volatility RV_t.

Discussion of assumptions The identification method proposed by Berger et al. (2020) improves the benchmark identification by separately identifying the genuine uncertainty shock as a news shock. Compared with other news shock identification schemes, such as the one

[14] Berger et al. (2020) acknowledge that they do not view the realized volatility shock as a structural shock since volatility on the stock market is driven by many different underlying shocks. One of these shocks could be the implied volatility shock, their main object of interest, which questions their identification scheme's validity. Since implied and realized volatility is very correlated, by ordering realized volatility first, we worry that the residual of implied volatility might not have enough variation to generate effects on the other variable in the system, including real activity, which might explain their puzzling results.

[15] The assumption of this approach excludes the transmission channel that an increase in uncertainty about the future, which manifests itself as an implied volatility shock, would lead to an increase in realized volatility today; the current identification scheme does not attribute it to the identified uncertainty news shock, but to the exogenous (and non-structural) shock to realized volatility.

[16] "[when] high volatility today predicts high volatility in the future."

in Barsky and Sims (2011), the BDG method does not define the uncertainty news shock as a shock that maximizes the forecast error variance of the targeted variable (realized volatility) but only pin down a linear combination of shocks that captures or generates changes in expectations of realized volatility over a specific horizon. In this sense, the uncertainty news shock identified in Berger et al. (2020) is not a news shock in the sense that it does not necessarily lead to significant shifts in future realized volatility but only shifts in people's prediction of future realized volatility based on current information.

In addition, Berger et al. (2020) further restricts the coefficient of the other variables' lags in the RV and IV equation is restricted to zero. They argue that this reduces the risk of overfitting. In other words, RV is assumed to be an AR(p) process, while IV is assumed to be a VAR(p) of RV and IV. We check the validity of this assumption across different assets in different periods. We find that for stock prices, the assumption is strongly rejected for the period before but not after the crisis. The difference suggests that in the post-crisis era, the stock market's performance is largely unhinged from the economic fundamentals . Applying the same test to gold and Euro-dollar, the assumption is strongly rejected in the post-crisis period. Therefore, we use the restricted model for stock volatility and the unrestricted model for gold and Euro-dollar[17].

Lastly, we compare the uncertainty news shock defined in this procedure and the implied volatility shock defined as the second column of the Cholesky matrix $\mathcal{S}$. We see that in the case of the restricted model, the BDG identification of uncertainty news shock is equivalent to the second shock of short-run identification.

4.2.4 Results

This section reports the results of the empirical exercises using the aforementioned identification methods. All VAR models below use four lags, with monthly data from 2008 to 2020, the period between the Great Recession and the Covid pandemic. As stated in the previous section, we use two sets of macro variables, following the conventional setup and the setup of Berger et al. (2020). We highlight three main findings: Improvements in identification methods, comparison across assets, and relationship with sentiment-related variables.

[17]See Appendix 4.6.3 for more details on the exogeneity text.

Comparison of Identification Methods

We start by comparing the identification results using the short-run method with a single uncertainty proxy and the methods of Berger et al. (2020), which employs both realized and implied volatility of one asset.

For the short-run identification, we use the *Financial Uncertainty Index* from Jurado et al. (2015) as the single uncertainty proxy as the benchmark since we want to compare the results with uncertainty shock identified using asset volatilities. *Macro Uncertainty Index* as a comparison. Throughout the exercise, we use the uncertainty indices computed over a one-month horizon, but the results are robust to changing to a three and twelve-month horizon. Figure 4.2 and 4.3 give the IRFs and the FEVDs. As can be seen from the figure, uncertainty shock identified using Financial Uncertainty Index has significant impacts on real variables. However, the effects are only half the size of the uncertainty shock identified using Macro Uncertainty Index. Nevertheless, uncertainty shock can still explain up to forty percent of the forecast error variances of both unemployment and industrial output. The results are robust to switching the macro variable to the conventional setup, as shown in Figure 4.26 and 4.27. It is worth noting that under this specification, financial uncertainty has more explanatory power over inflation than the macro uncertainty index, suggesting that the financial uncertainty index contains more forward-looking information on price level variations. Overall, the findings are consistent with the empirical studies of uncertainty shock.

Next, we apply the approach of Berger et al. (2020) to our data sample from 2008 to 2019. Figure 4.4 and 4.5 report the dynamic responses of real activity (industrial production and unemployment) to the uncertainty news shock. As a comparison, Figure 4.6 and 4.7 report the results of the so-called surprise shock.

The figures show that once we separately examine current and future uncertainty, their impacts are significantly different. In Figure 4.4, we observe that an increase in future uncertainty leads to a persistent decrease in industrial production and a persistent increase in unemployment. In contrast, the realized volatility shocks, or uncertainty surprise shock, generates much less response from real variables as in Figure 4.6. The results go against the finding in Berger et al. (2020) whereby they find a muted response of industrial production and employment to an increase in future uncertainty, whereas the realized volatility shocks, which they argue is not a structural shock, lead to significant real effects. Our results are in line with previous results in the literature that finds that an increase in options implied volatility leads to declines in output (Bloom (2009), Basu and Bundick (2017) and Leduc and

Liu (2016)).

Comparing the results of the two identification methods, we can see that the responses of real variables (industrial output and unemployment) are both significant, and their FEVDs are at similar levels (around thirty percent)[18]. However, the size of the response to the stock uncertainty news shock is smaller, which is also intuitive, as the Financial Uncertainty Index presumably captures not only information on the stock market but also on other assets. The only difference is the responses of the policy rate, as stock uncertainty news shock generates a positive response from the policy rate, as opposed to Financial Uncertainty Index. The difference can be due to the decoupling of news and surprise shock, as we can see that the uncertainty surprise shock still generates a negative response. Alternatively, the results can indicate asset-specific characteristics captured in the volatility and reflected in the uncertainty shock identified, which we examine in the next section.

Assets-specific Uncertainty

We now examine the asset-specific characteristics in the uncertainty shocks identified using the BDG method. In particular, we contrast the identification results using stock volatility to that of another asset: gold[19]. The results of the uncertainty news shocks identified using gold volatilities are reported in Figure 4.8 and 4.9. Figure 4.10 and 4.11 report the results of the surprise shock.

The figures show that gold uncertainty news shock has a significantly larger impact on real variables. The unemployment and industrial output responses are around half of the size of the responses in the benchmark identification case, and the FEVDs are also of similar levels. In addition, the response of policy rates is negative and approximately the same size. The results contrast sharply with that of the stock uncertainty shock.[20] On the other hand, the uncertainty surprise shock does not have significant real impacts, similar to the case of stock.

The fact that the same identification methods generate different results when switching between asset classes indicates that different assets' volatilities contain different information

[18]Note that the figure shows the FEVD of the uncertainty news shock that has not been orthogonalized.

[19]As a comparison, we also use Euro-dollar foreign exchange and oil. The results are shown in Appendix 4.6.3

[20]Some may argue that the response difference is because stock implied volatility is larger than gold. However, as shown in Table 4.2, the implied volatilities of stock and gold are pretty close. In addition, one can argue that the difference is because we use the restricted model for stock and the unrestricted model for gold. In robustness tests, we find that while switching to the restricted model does sharply reduce the real effect of the gold uncertainty shock, using the unrestricted model for stock volatilities does not significantly increase the real effects of stock uncertainty shock. Therefore, the test we perform for the model choices is valid and is not the main driver for the result differences.

regarding economic uncertainty. Referring to the framework in Section 4.2.1, the differences can be due to several channels: First, different assets' volatilities contain different amounts of fundamental uncertainty. As shown by the tests for the restricted model, stock market volatilities in the post-crisis era seem independent of the economic fundamentals. Second, asset volatilities might reflect asset-specific uncertainty that does not arise from the domestic economy but has real effects. For instance, both oil and foreign exchange can be driven by global market situations. Lastly, asset-specific characteristics can affect non-fundamental factors such as expectation error or biases. For instance, stock market turbulence entirely due to arbitraging activities can change the mentality of the investors, including high-income households and large institutions, which then generates a real impact on the economy via portfolio adjustments. Similarly, temporary oil price disruption may also generate panic and leads to real economic consequences. We investigate these impacts in the next section.

Sentiment Responses

Finally, we investigate the heterogeneity in the uncertainty shocks from the perspective of sentiment-related variables, which sheds light on the link between second-order moments and non-fundamental factors.

We start with benchmark identification, with Financial Uncertainty Index as the single uncertainty measure and Michigan Consumer Inflation Expectation as the sentiment measure. Figure 4.12 and Figure 4.13 report the result impulse response functions and forecast error variance decomposition. The figures show that while the uncertainty shock identified has little explanatory power over the Consumer Inflation Expectation, adding the index to the model significantly attenuates the responses of real variables to uncertainty. The results are robust to switching to the conventional setup and changing the uncertainty measure to Macro Uncertainty Index, as shown in Figure 4.28 to Figure 4.31 in Appendix 4.6.3.

We now move on to the BDG identification with dual uncertainty proxies. For this setup, we use gold as the asset and Michigan Consumer Sentiment Index as sentiment measurement. As shown in Figure 4.25, the implied volatility of gold is highly negatively correlated with the Michigan Consumer Sentiment Index, which suggests a potential link between second-order uncertainty and non-fundamental factor. Figure 4.14 to 4.17 give the results for the identification. We can see that the uncertainty shock also attenuates the responses and FEVDs of the gold uncertainty shock, although the effect is insignificant. More importantly, uncertainy news shocks lead to a contemporaneous and persistent decrease in consumer sentiment.

The interpretation is that uncertainty about the future can weigh in on economic agents' perception of the current situation, leading to an underestimation of the economic condition. Interestingly, when comparing the effect of uncertainty news shocks to surprise shocks, we find that the surprise shocks generate a more significant response on impact. However, the effect quickly disappears within several periods. Interestingly, an exogenous increase in future uncertainty as measured by implied volatility on the stock market is accompanied by an increase in consumer sentiment on impact, a counterintuitive result since this implies a boost of optimism, even though the index gradually falls and becomes more in line with the contractionary economic activity. While the reaction to the impact of consumer sentiment might suggest the further scope of the better-identifying uncertainty shock, the muted reaction of the federal funds rate suggests that the effect on activity comes from the future uncertainty shock and not from an exogenous monetary policy shock due to misspecification or the endogenous response of monetary policy to an increase in uncertainty about the future.

For the last set of exercises, we use stock as the asset and the excess bond premium as sentiment measurement. The results are shown in Figure 4.18 to 4.21. Like the gold shock, the stock uncertainty news shock increases risk aversion in the bond market, as indicated by a rise in the excess bond premium.

4.2.5 Future Directions

The takeaway from these exercises is that the current identification of uncertainty shocks potentially mixes several different types of uncertainty; most notably, we suspect that the shock identified is not purged from the sentiment shocks or that the uncertainty shock affects the real economy via a channel of sentiment. The results call for the next step of providing a more robust identification strategy that explores the heterogeneity in the uncertainty.

To achieve this goal, we propose several alternative identification methods developed based on the identification scheme Berger et al. (2020). To start with, to separate asset-specific uncertainty from fundamental uncertainty, we propose two methods. The first method is straightforward: Applying the principal component analysis of the four groups of assets' implied volatility, we obtain the common component and use it in place of asset-specific implied volatility. In the second method, we incorporate the proxy identification methods. Using one asset's implied volatility as the proxy of another asset's implied volatility, we obtain fitted values of volatility that are orthogonal to asset-specific components. We then implement this fitted value in the Berger et al. (2020) identification scheme to examine the results.

4.3 Theoretical Framework

This section presents a simple analytical framework consistent with the main empirical findings. That is, (1) asset-volatilities reflect both asset-specific uncertainty and fundamental uncertainty of the economy; (2) asset volatilities contain information on sentiment-related variables, such as consumer sentiments and investors' risk appetite. Using this framework, we can further shed light on the mechanism behind asset volatilities and economic outcomes.

The key mechanism is noisy information, i.e., the agents do not have enough information to distinguish between asset-specific shocks and economic shocks. Under this simple assumption, the equilibrium asset price volatilities can consist of uncertainty arising from economic fundamentals and market-specific characteristics. In addition, with additional errors in the expectation process, the observed volatility also reflects sentiment or risk appetite variations.

4.3.1 Model Setup

Based on the general asset-pricing equation in Section 4.2, we build a two-period toy model of an endowment economy à la the model of Miao et al. (2021) to pin down further how each component contributes to asset price variations. To start simple, we assume that risk aversion is a constant parameter. Assume that the utility function of the agents is given by

$$\mathcal{E}_i\left[\frac{C_{i1}^{1-\gamma}}{1-\gamma}+\beta\frac{C_{i2}^{1-\gamma}}{1-\gamma}\right], \tag{4.3.1}$$

where

$$\mathcal{E}_i(\cdot)=\mathbb{E}_i(\cdot)U_i.$$

$\mathbb{E}_i$ denotes rational expectation operator, and $\mathcal{E}_i$ is behavioral expectation subject to shock U_t. This specification has been used in the asset-pricing model in Hassan and Mertens (2017), in which U_i denotes the forecast errors agents make when forming their expectations, which can be homogeneous or heterogeneous across agents. Here, we assume that the component U_i can be anything that alters agents' expectations, including but not restricted to prediction errors[21].

[21] An alternative explanation for this component is time-varying rare disaster probability. Gabaix (2012) provides an analytical framework based on time-varying rare disaster probability, which can be illustrated as

$$\mathcal{E}_i(x_t)=\mathbb{E}_i(x_t)+\Delta_p(\sigma^2)(\underline{x}-\bar{x})=(1-p)\bar{x}+p\underline{x}+\Delta_p(\sigma^2)(\underline{x}-\bar{x})$$

where $\Delta_p(\sigma^2)$ is adjustment of probability of rare disaster.

The log-linearized pricing equation under this two-period setup can be expressed by

$$p = \mathbb{E}_i[d] + \mathbb{E}_i[m_i] + u + v_i \tag{4.3.2}$$

where $u + v_i = \log U_i$, u and v_i are independent normal random variables with means zero and variances σ_u^2 and σ_v^2. The budget constraint is given by

$$C_{i1} + QS_i = Q + L_i, \quad C_{i2} = DS_i$$

where Q and S_i denote the asset price and shareholdings, respectively. The initial level of shareholding is normalized to one. The dividends and labor income satisfy

$$\log D = \log \bar{D} + x_d\varepsilon_a + \kappa x_l \varepsilon_l, \quad \log L_i = \log \bar{L} + x_l\varepsilon_l$$

where $\bar{D}, x_d, \bar{L}$, and x_l are fixed parameters, and ε_a and ε_i are independent normal random variables with means zero and variances σ_a^2 and σ_i^2. $\kappa \in (0,1)$ captures the extent to which the asset dividends pick up the fundamental shocks in the economy[22].

Importantly, we assume that dividend process shock and labor income shock are not perfectly observable to agents. Instead of separately observing ε_a and ε_l, they receive only one signal that combines the two shocks, $x = \varepsilon_a + \varepsilon_l$. The assumption is intuitive. The agents in the economy are exposed to the latest developments in asset markets via daily news. At the same time, most of them cannot fully understand whether asset price variations are due to economic fundamentals or particular issues in a particular market, such as supply chain disruption and speculative bubbles. For instance, during the Covid pandemic, there has been unusual turbulence in oil prices and stock market performance. Households have difficulty interpreting whether it is due to temporary disruptions or the underlying economic system malfunctioning. As a result, agents need to infer the true underlying shocks based on one exogenous signal, x, and one endogenous signal, price Q of the asset. The equilibrium asset price thus contains information on the asset-specific uncertainty, captured by the dividend shock ε_a, and the fundamental uncertainty of the economy, captured by ε_l. Additionally, with the presence of U_t, the inference process will also be affected by the homogenous part of the

[22] One might argue that the dividend process shock ε_a itself entails information on the economic fundamental, not just the ε_l shock. For instance, asset dividends contain information on the profit situation of firms, which are the production sector of the economy. Therefore, in this specification, we interpret ε_a as the part of the information contained in the dividend process that is purely about the behavior of the market participants that is orthogonal to the economy fundamental, and all the effects of economic fundamentals on the dividend process is captured by $\kappa x_l \varepsilon_l$.

expectation deviations, which can be prediction errors or sentiment.

The timing is as follows. The agents receive both the exogenous signal and the price Q of the asset. Having updated the information, the agents choose asset holdings at the beginning of period one. Then, after the labor income shock is realized at the end of period one, they choose period-one consumption C_{i1}. At the end of period two, all shocks realize, and the agent i decides on consumption C_{i2}.

4.3.2 Solution

We sketch the key steps of the solution to the toy model. Under the two-period setup, the optimal asset holding is given by

$$s_i = \frac{\mathbb{E}_i[(1-\gamma)d] - q + u + v_i}{\gamma(1+\bar{Q}/\bar{L})} + \frac{\mathbb{E}_i\left[l_i\right]}{1+\bar{Q}/\bar{L}} \tag{4.3.3}$$

The price is then pinned down by the market clearing condition $\int_I s_i di = 0$

$$q = (1-\gamma)\overline{\mathbb{E}}[d] + \gamma\overline{\mathbb{E}}\left[l_i\right] + u \tag{4.3.4}$$

where $\overline{\mathbb{E}}[\cdot] \equiv \int \mathbb{E}_i[\cdot]di$. Without idiosyncratic shocks, $\overline{\mathbb{E}}[\cdot] = \mathbb{E}_i[\cdot]$. The asset volatility is thus

$$Var(q) = (1-\gamma)^2 Var(\overline{\mathbb{E}}[d]) + \gamma^2 Var(\overline{\mathbb{E}}\left[l_i\right]) + \sigma_u^2 \tag{4.3.5}$$

To compute the expectation terms $\mathbb{E}_i[d]$ and $\mathbb{E}_i\left[l_i\right]$, we use the guess-and-verify method. Suppose that the price q is linearly dependent on the shocks.

$$q = q_a\varepsilon_a + q_l\varepsilon_l + q_u u \tag{4.3.6}$$

which is informationally equivalent to $\hat{q} = \varepsilon_a + (q_l/q_a)\varepsilon_l + (q_u/q_a)u = \varepsilon_a + \hat{\varepsilon}_l + \hat{u}$. The variance of the asset price is given by

$$Var(q) = q_a^2\sigma_a^2 + q_l^2\sigma_i^2 + q_u^2\sigma_u^2 \tag{4.3.7}$$

From the expression, we can see that the informational content of asset price volatility is impacted by the degree to which agents are unable to differentiate between fundamental and market-specific uncertainty and the presence of prediction errors. Like γ, the stochastic components impact price volatilities through two channels: directly via changing the variance size and indirectly via changing the coefficients, representing changes in agents' expectation formation.

To solve for the expression of q_a, q_l, and q_u, we take this linear form of q and apply the Gaussian Projection Theorem to obtain the expression for $\overline{\mathbb{E}}[\varepsilon_a]$ and $\overline{\mathbb{E}}\left[\varepsilon_l\right]$.

$$\begin{aligned}\overline{\mathbb{E}}[\varepsilon_a] = \mathbb{E}_i[\varepsilon_a] =& \tau_q\hat{q} + \tau_x x\\ \overline{\mathbb{E}}\left[\varepsilon_l\right] = \mathbb{E}_i\left[\varepsilon_l\right] =& -\tau_q\hat{q} + (1-\tau_x)\, x\end{aligned}$$

where τ_q and τ_x are pinned down by the variance terms ε_a, ε_l, and ε_u. Taking $\overline{\mathbb{E}}[\varepsilon_a]$ and $\overline{\mathbb{E}}[\varepsilon_l]$ back to the expressions of $\mathbb{E}_i[d]$ and $\mathbb{E}_i\left[l_i\right]$, we get

$$\begin{aligned}\overline{\mathbb{E}}[d] = \mathbb{E}_i[d] =& (x_d - \kappa x_l)\tau_q\hat{q} + (x_d\tau_x + \kappa x_l\,(1-\tau_x))x\\ \overline{\mathbb{E}}[l_i] = \mathbb{E}_i\left[l_i\right] =& -x_l\tau_q\hat{q} + x_l\,(1-\tau_x)\,x\end{aligned} \tag{4.3.8}$$

Taking these expressions into Equation 4.3.4 yields

$$\begin{aligned}q =& \left[(1-\gamma)x_d\tau_a + ((1-\gamma)\kappa+\gamma)\,x_l\tau_i\right]\varepsilon_a\\ &+ \left[(1-\gamma)g_u\tau_q x_d - ((1-\gamma)\kappa+\gamma)\,g_u\tau_q x_l + 1\right]u\\ &+ \left[(1-\gamma)x_d\tilde{\tau}_a + ((1-\gamma)\kappa+\gamma)\,x_l\tilde{\tau}_i\right]\varepsilon_l\end{aligned}$$

where $\tau_a = \tau_q + \tau_x \in (0,1)$ $\tau_i = 1 - \left(\tau_q + \tau_x\right)$, $\tilde{\tau}_a = g_l\tau_q + \tau_x$, and $\tilde{\tau}_i = 1 - \left(g_l\tau_q + \tau_x\right)$. Comparing the coefficients pins down the price q. Taking q back to Equation 4.3.3 yields the holding, which depends only on idiosyncratic forecast errors. The detailed proof can be found in Appendix 4.6.4.

4.3.3 Discussion

Fundamental vs. Asset Uncertainty

To see more clearly the variances of the underlying shocks affect price, we first mute the homogeneous expectation deviation u. In this case, the functional form of q becomes $q = q_a\varepsilon_a + q_l\varepsilon_l$. Define $g = q_l/q_a$. We have the following expression for q, with detailed results in Appendix 4.6.4

$$q = \left[(1-\gamma)x_d\tau_a + ((1-\gamma)\kappa+\gamma)\,x_l\tau_i\right]\varepsilon_a + \left[(1-\gamma)x_d\tilde{\tau}_a + ((1-\gamma)\kappa+\gamma)\,x_l\tilde{\tau}_i\right]\varepsilon_l \tag{4.3.9}$$

Matching coefficients yields the following cubic equation in g

$$0 = \left[(1-\gamma)x_d\sigma_a^2 + ((1-\gamma)\kappa+\gamma)\, x_l\sigma_l^2\right](g^3-g^2) + ((1-\gamma)\kappa+\gamma)\, x_l\sigma_a^2(g-1)$$

We have $g = \{1, \frac{\mathcal{A}\pm(\mathcal{A}^2-4\mathcal{A}\mathcal{B})^{1/2}}{2\mathcal{A}}\}$, where $\mathcal{A} = \left[(1-\gamma)x_d\sigma_a^2 + ((1-\gamma)\kappa+\gamma)\, x_l\sigma_l^2\right]$ and $\mathcal{B} = ((1-\gamma)\kappa+\gamma)\, x_l\sigma_a^2$. The solution shows that even without the presence of prediction errors, the degree to which stock prices and volatilities reflect fundamental economic uncertainty is not deterministic, but depends on the information extraction activities of the agents.

Risk Appetite

Our empirical findings show that an uncertainty shock identified using asset volatility can lead to an increase in risk aversion or a decrease in risk appetite. Under the current framework, the risk-aversion parameter γ affects asset volatility through multiple channels. From Equation 4.3.5, asset volatility consists of three components: variance of expected dividend, expected income, and expectation error. Note that the risk-aversion parameter γ governs the degree to which asset volatility is affected by dividend and stochastic volatility. When risk aversion is low, i.e., γ is close to zero, the asset volatility is less affected by the variance of the fundamental economic uncertainty. In the meantime, the size of the variances of two expectation terms also depends on γ, which we will show in the proof below. As a result, risk-aversion affects asset volatility via two channels: Changing the weights of the variance of the agents' expectations of the dividend and the income process and directly changing the sizes of these variances. The overall impact of γ on asset volatility is thus ambiguous.

4.3.4 Future Directions

Prediction Error

In the baseline model, the prediction errors are exogenous, and thus they do not contribute or respond to the variations of asset volatility. An alternative possibility is that the prediction error is not invariant and is affected by the uncertainty in the economy. This possibility is consistent with our empirical findings that consumer sentiment index responses to uncertainty shocks, which indicates that second-order moment shock potentially changes agents' subjective perceptions of the economy. The interpretation is that people become more pessimistic and underestimate future incomes and consumption in high uncertainty times and vice versa.

To illustrate the idea, we assume the following form of specification for the error term

$$\mathcal{E}_i(\cdot) = \mathbb{E}_i(\cdot) + \xi(\boldsymbol{\sigma}^2).$$

where, similar to $\log(U_t)$, the term $\xi(\sigma^2)$ captures the difference between rational expectation $\mathbb{E}_i(\cdot)$ and the actual expectation of the agents, $\mathcal{E}_i(\cdot)$. The difference is that we assume $\xi(\boldsymbol{\sigma}^2) \sim \mathcal{N}(\bar{\xi}(\boldsymbol{\sigma}^2), \sigma_\xi(\boldsymbol{\sigma}^2))$, where the mean and variances depend on underlying uncertainties in the model $\boldsymbol{\sigma}^2 = \{\sigma_a^2, \sigma_l^2\}$. Therefore, a higher uncertainty can translate into a higher level of bias in the estimation.

This reduced-form assumption can be rationalized by the theory of diagnostic expectation in Bordalo et al. (2020). The mechanism can be illustrated as follows. Suppose x_t is a hidden state that evolves according to an AR(1) process $x_t = \rho x_{t-1} + u_t$, where u_t is a normal shock with mean zero and variance σ^2, and $s_t = x_{t-1} + \varepsilon$ is a noisy signal of $x_{t-1} \sim \mathcal{N}(\bar{x}_{t-1}, \sigma^2)$. The diagnostic expectation is given by

$$\mathcal{E}_i(x_t) = \mathbb{E}_i(x_t) + \theta \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2} (s_t - x_{t-1}) = \bar{x}_{t-1} + \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2} (s_t - x_{t-1}) + \theta \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2} (s_t - x_{t-1})$$

The parameter θ governs the extent to which the expectation is biased upwards or downwards, depending on whether the signal is above or below its expected level. From the expression, we can see that the size and variance of the prediction error are endogenous in the variance of the state variable and noise terms. Therefore, the theory provides a micro-foundation for the ad hoc assumption of uncertainty-dependent prediction error, and further research is needed to understand this mechanism's implications better.

Dispersed Information

So far in the model, we assume the fundamental uncertainty to be an aggregate shock. If the fundamental uncertainty consists of an idiosyncratic component, for example, when the agents face idiosyncratic income shock, $L_i = \log \bar{L} + x_l(\varepsilon_l + \varepsilon_{il})$, the impact of fundamental uncertainty on asset volatility will be different. More importantly, once we extend the simple model to an infinite-horizon setup, the dispersed information generates higher-order expectations. This offers another to examine the role of sentiment, as recent research associates negative sentiment, or lack of confidence, with failures of coordination with the presence of higher-order expectations (Angeletos et al., 2018). Therefore, extending the benchmark model to a dispersed information environment is necessary for the understanding of the correlation between second-order moment shocks and sentiment responses in the form of higher-order expectations.

4.4 Conclusion

This paper joins the debate on the role of aggregate uncertainty in causing contractions in real economic activity. Empirically, we build on the current identification methods of uncertainty, in particular Berger et al. (2020), which stresses the distinction between realized volatility and uncertainty about the future. We provide novel findings applying their identification scheme to different assets' volatilities and examine causes of the results. Theoretically, we utilize an analytical framework of asset pricing with noisy information that sheds light on the mechanism behind the empirical findings.

Our benchmark is the standard approach in the literature of uncertainty shock identification, where only one measure of uncertainty is used in a structural VAR. We use the Financial Uncertainty Index in Jurado et al. (2015), a measure of uncertainty based on implied volatilities of multiple financial time series and thus comparable to the asset volatilities we use in the following exercises. We study the effect of identified uncertainty shocks on real activity and find that uncertainty shocks cause a deep and short contraction in output. Nevertheless, the effects are attenuated once we include inflation expectations, a first-order term. This leads us to conclude that the uncertainty shocks identified are potentially related to first-order moments.

Following the recent developments in the (Bloom (2009)), we move on to use pairwise volatility, namely realized and implied volatility, of the individual asset to further decouple uncertainty shocks into news shocks about the future and current period surprises. We find that shocks to the implied volatility of stock prices, as identified a la BDG, cause a persistent contraction in output, in contradiction to BDG, and. When studying the effect of shocks on the implied volatility of gold prices, we confirm that second-moment shocks negatively affect real activity. The impact is even more substantial than that of stock uncertainty shock. Moreover, the gold uncertainty shocks are accompanied by an increase in pessimism. We interpret this as building the case for the need to separately and jointly identify sentiment and uncertainty shocks to better understand the role of expectations about the future in driving contraction in output.

Lastly, we provide a simple asset-pricing framework with noisy information to illustrate the mechanism behind the empirical finding, particularly how fundamental uncertainty, asset-specific characteristics, and non-fundamental factors such as sentiment and risk-aversion contribute jointly to asset volatilities.

As a next step, we plan to improve on the current identification methods to separate the effect of uncertainty shock and sentiment responses and compare the results to the simulation results of the asset pricing models in order to further shed light on the link between financial asset volatilities and uncertainty in the economy.

4.5 Figures

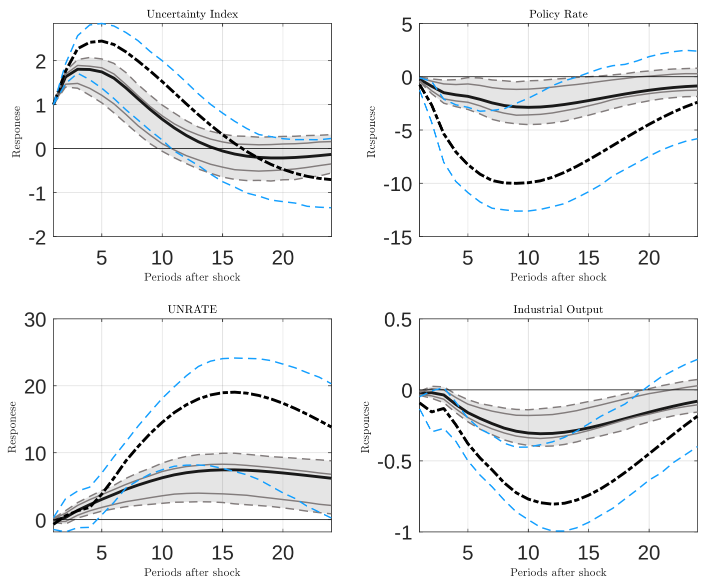

Figure 4.2: IRF to Uncertainty Shock (2008 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty shock using Financial Uncertainty Index (solid line) and Macro Uncertainty Index (dashed line) from Jurado et al. (2015). Sample is from 2008 Jan to 2019 Dec. The shaded area shows [16, 86] and [5, 95] percent confidence interval for the uncertainty shock using financial uncertainty index.

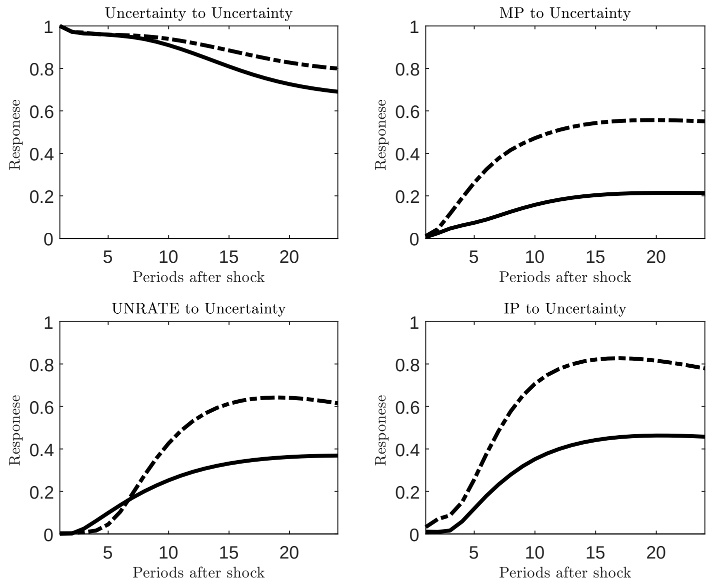

Figure 4.3: IRF to Uncertainty Shock (2008 Jan-2019 Dec)

Note: The figure shows the FEVDs to identified uncertainty shock using Financial Uncertainty Index (solid line) and Macro Uncertainty Index (dashed line) from Jurado et al. (2015).

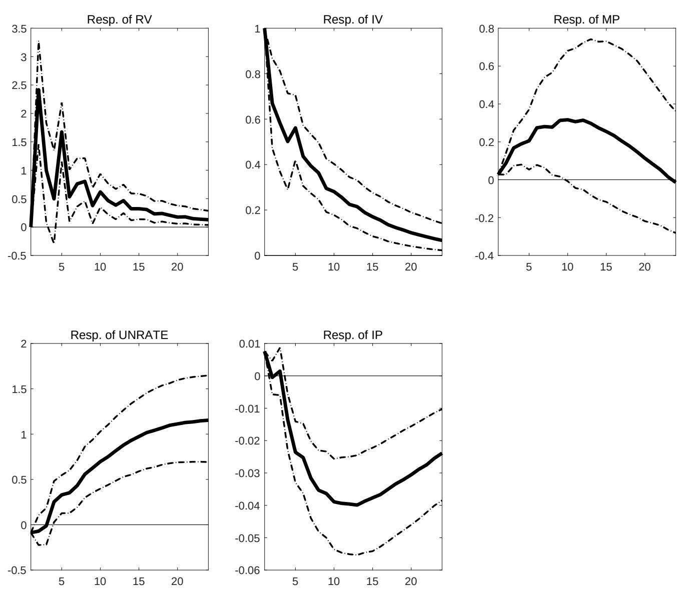

Figure 4.4: IRF to Uncertainty News Shock (2008 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty news shock à la Berger et al. (2020), using realized and implied volatilities of stock index with restricted model.

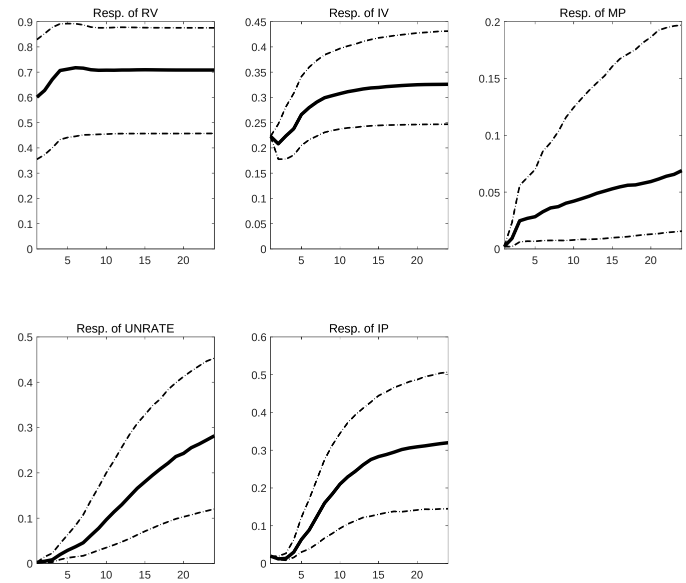

Figure 4.5: FEVD to Uncertainty News Shock (2008 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty news shock (not orthogonalized to RV) à la Berger et al. (2020), using realized and implied volatilities of stock index with restricted model.

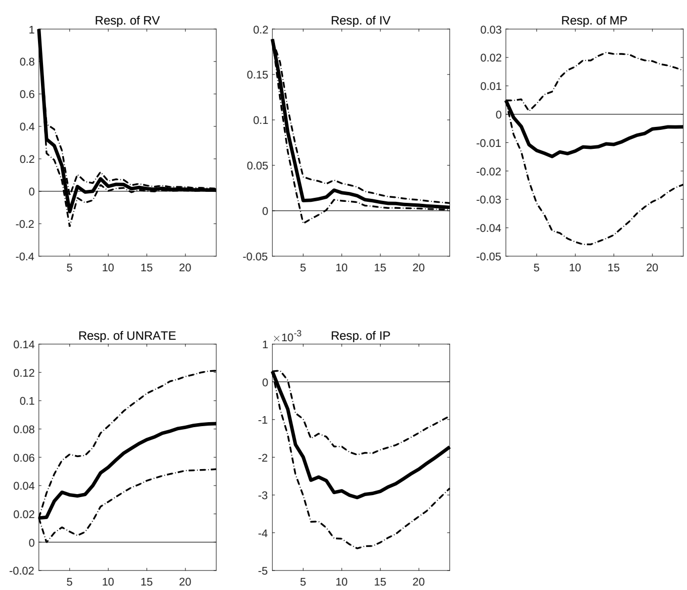

Figure 4.6: IRF to Uncertainty Surprise Shock (2008 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of stock index with restricted model.

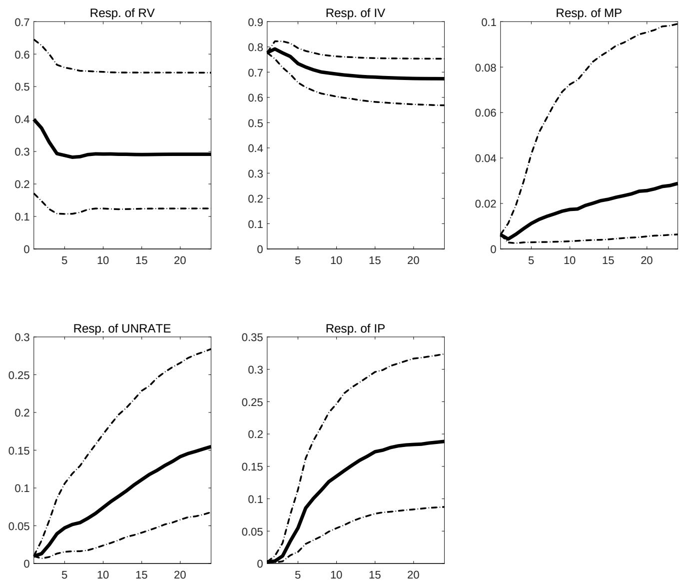

Figure 4.7: FEVD to Uncertainty Surprise Shock (2008 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of stock index with restricted model.

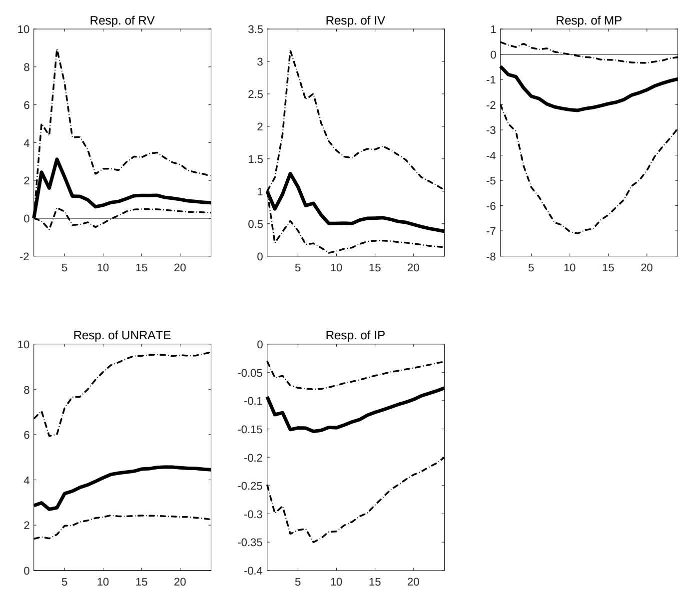

Figure 4.8: IRF to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty news shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

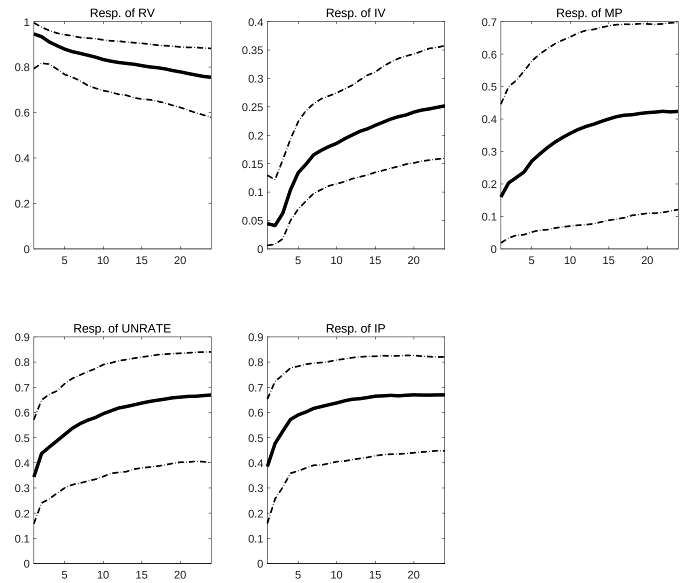

Figure 4.9: FEVD to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty news shock (not orthogonalized to RV) à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

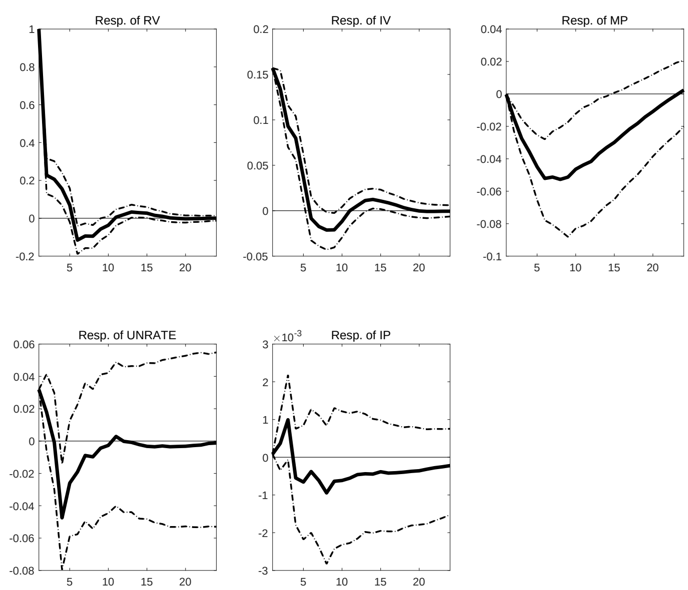

Figure 4.10: IRF to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

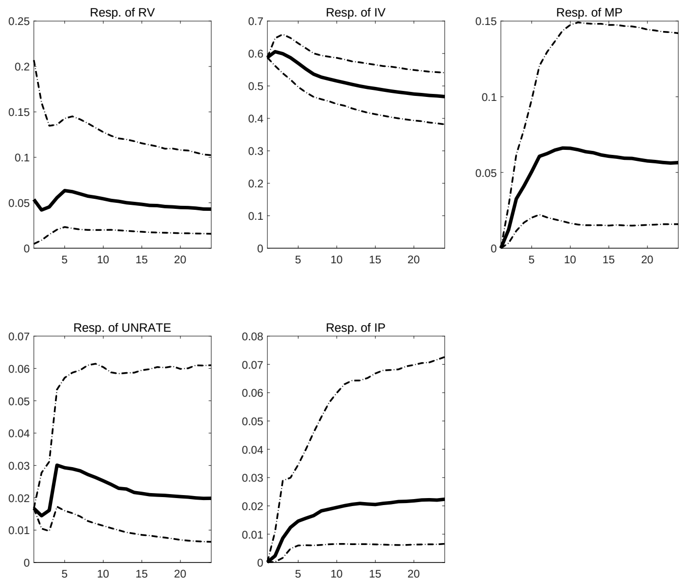

Figure 4.11: FEVD to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

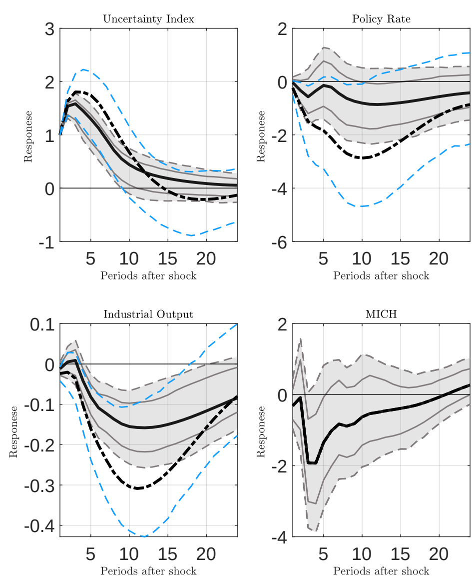

Figure 4.12: IRF to Uncertainty Shock (2008 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and without Michigan Consumer Index (dashed line). Sample is from 2008 Jan to 2019 Dec. The shaded area shows [16, 86] and [5, 95] percent confidence interval for the uncertainty shock using financial uncertainty index.

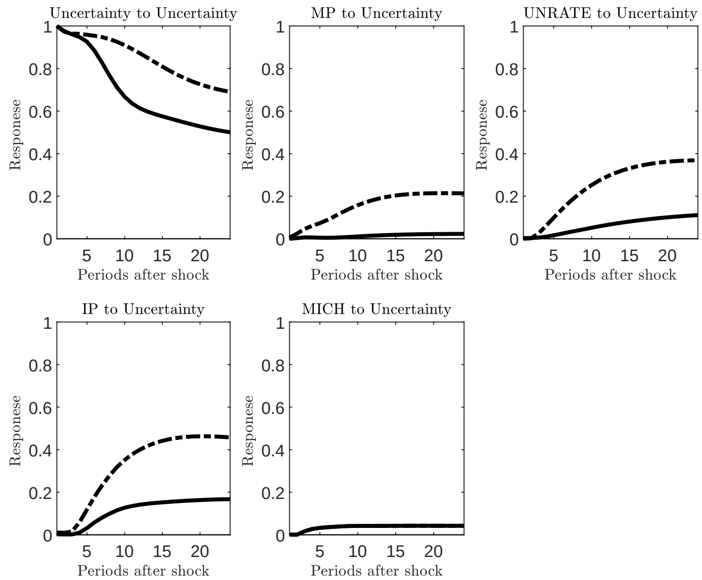

Figure 4.13: IRF to Uncertainty Shock (2008 Jan-2019 Dec)

Note: The figure shows the FEVDs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and without Michigan Consumer Index (dashed line).

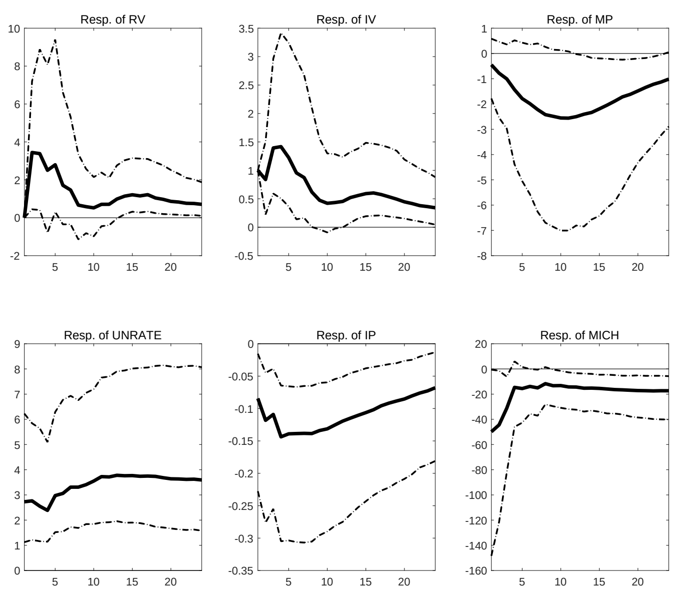

Figure 4.14: IRF to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty news shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

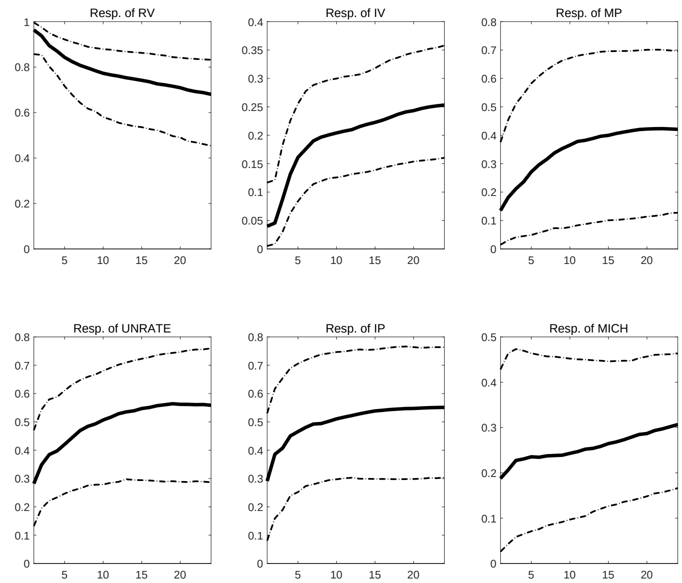

Figure 4.15: FEVD to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty news shock (not orthogonalized to RV) à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

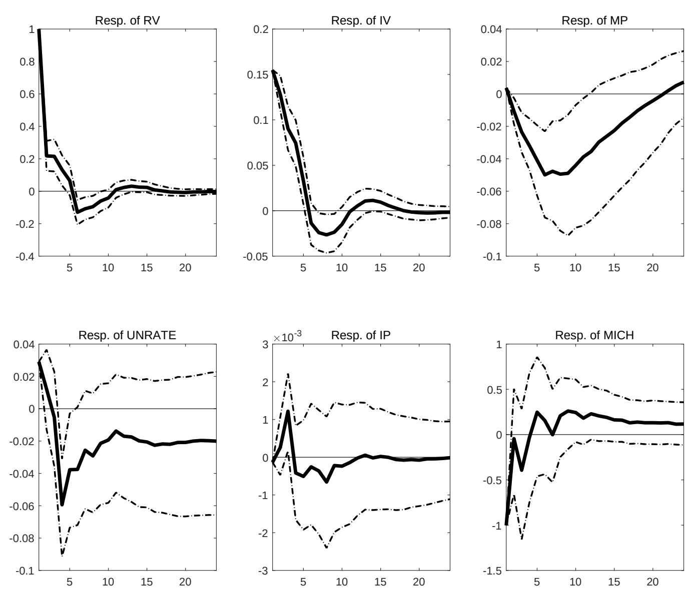

Figure 4.16: IRF to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

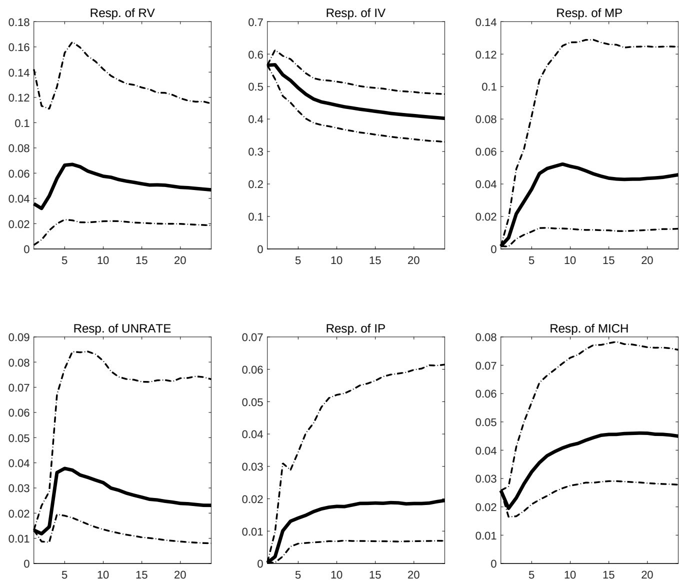

Figure 4.17: FEVD to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of gold with unrestricted model.

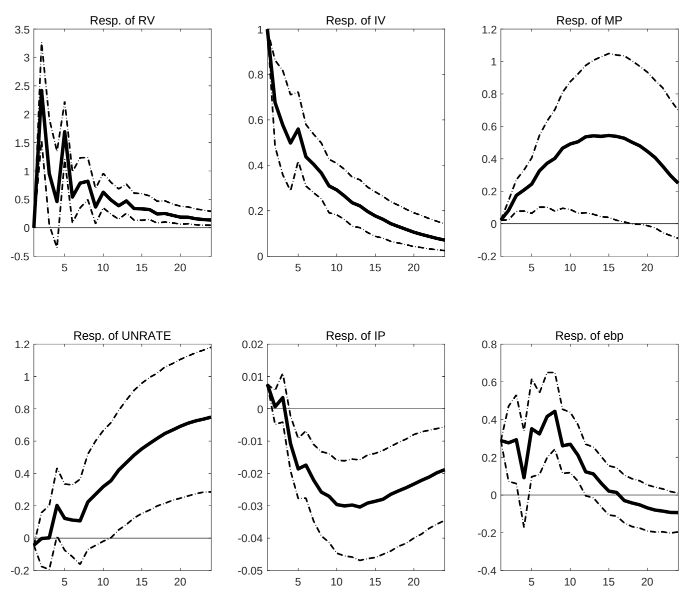

Figure 4.18: IRF to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty news shock à la Berger et al. (2020), using realized and implied volatilities of stock with restricted model.

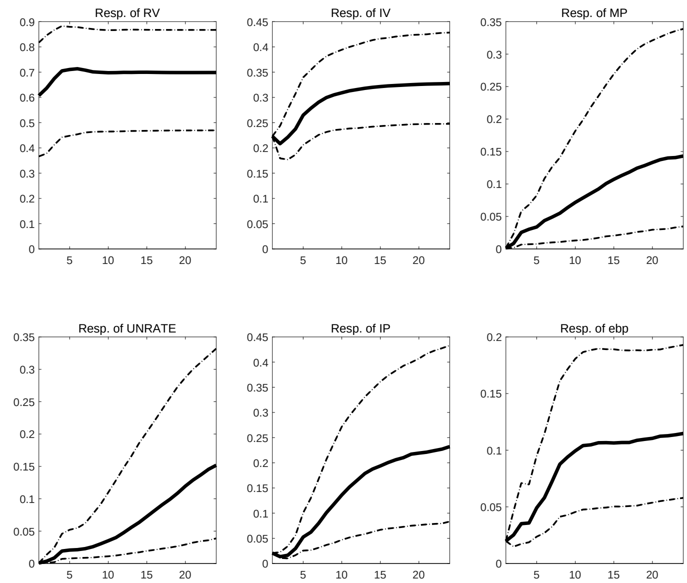

Figure 4.19: FEVD to Uncertainty News Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty news shock (not orthogonalized to RV) à la Berger et al. (2020), using realized and implied volatilities of stock with restricted model.

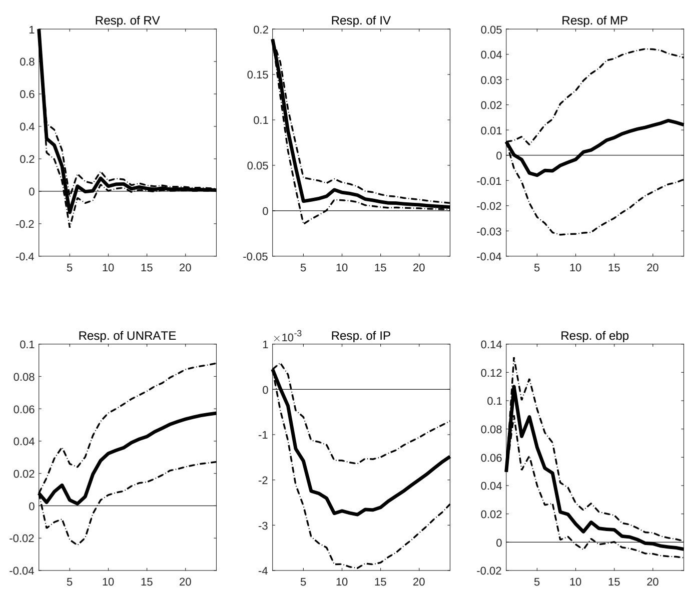

Figure 4.20: IRF to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the IRFs to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of stock with restricted model.

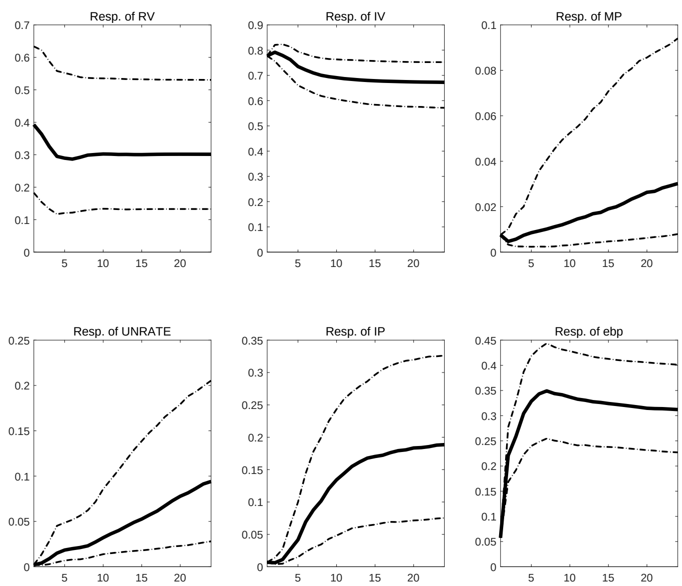

Figure 4.21: FEVD to Uncertainty Surprise Shock (2009 Jan-2019 Dec)

Note: The figure shows the FEVD to identified uncertainty surprise shock à la Berger et al. (2020), using realized and implied volatilities of stock with restricted model.

4.6 Appendix

4.6.1 Uncertainty Measurement

Uncertainty measurements can be broadly classified into second-order moments, text-based-, and survey-based measurements.

Second-order Moments

The most frequently used proxies for uncertainty is the second-order moment of a distribution, including volatilities of macro variables and financial assets (Jo, 2014; Alessandri et al., 2020; Berger et al., 2020; Jurado et al., 2015; Alessandri and Mumtaz, 2019), and cross-sectional dispersion (Bloom, 2009; Dew-Becker and Giglio, 2020).

The volatility measurements can be further classified into realized volatility and implied volatility. The former is the volatility computed using the prices observed, and the latter is the real-time estimation of an asset's price as it trades computed using option prices. In our analysis, for implied volatility, we use directly the indices calculated from options prices by the Chicago Board Options Exchange (CBOE). For stocks, we use the Volatility Index (VIX) [23] measures market expectation of near-term volatility conveyed by stock index option prices. For gold prices, we use the CBOE Gold ETF[24] Volatility Index.[25]. For oil prices, we use the CBOE Crude Oil ETF Volatility Index .[26] Lastly, we use the CBOE EuroCurrency ETF Volatility Index for the euro-dollar exchange rate. [27] The time coverage of the variables used is reported in Table (4.3).

Text-based Measurement

A more recent strand of this literature seeks to measure uncertainty by applying the text analysis method to news reports. Examples include Baker et al. (2016) and Husted et al. (2020) for monetary policy uncertainty, Caldara et al. (2020) for trade policy uncertainty, and Ahir et al. (2018) for a series of country-specific uncertainty index.

[23]Chicago Board Options Exchange, CBOE Volatility Index: VIX [VIXCLS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/VIXCLS, August 20, 2022.

[24]"Exchange Traded Funds (ETFs) are shares of trusts that hold portfolios of stocks designed to track the price performance and yield of specific indices closely."

[25]Chicago Board Options Exchange, CBOE Gold ETF Volatility Index [GVZCLS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GVZCLS, August 20, 2022.

[26]Chicago Board Options Exchange, CBOE Crude Oil ETF Volatility Index [OVXCLS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OVXCLS, August 20, 2022.

[27]Chicago Board Options Exchange, CBOE EuroCurrency ETF Volatility Index [EVZCLS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/EVZCLS, August 20, 2022.

Compared to the second-order moments that rely on economic and financial data collection, the text-based approach of uncertainty measurements captures the uncertainty of a broader context that otherwise cannot be measured by data. For instance, this category's most frequently used index, the Economic Policy Uncertainty (EPU) constructed by Baker et al. (2016), reflects the agents' contemporaneous perception of the economic policy. The authors develop a database of economic policy uncertainty indices based on newspaper coverage frequency. They construct an index from three underlying components to measure policy-related economic uncertainty. The first and most flexible component quantifies newspaper coverage of policy-related economic uncertainty. [28] The authors argue that the index proxies for policy-related uncertainty, as shown by the evidence from the experiment of human readings of 12,000 newspaper articles. A higher value of this index indicates a higher value of reported policy-related uncertainty. In addition, recent research presents text-based measures that bridge the gap between text-based and volatility measures Baker et al. (2019).

Survey Data Measurement

The last strand of measurements comes from the survey conducted towards professionals and consumers regarding their perception of the economy, such as the Survey of Professional Forecasters (SPF), New York Fed Survey of Consumer Expectation(SCE), Philadelphia Fed's Business Outlook Survey (BOS), and IFO Business Climate Survey (IFOBCS). Recent literature that employs or studies survey-based uncertainty includes **?**, Coibion et al. (2020) and Coibion et al. (2021)),

4.6.2 Stylized Facts

Data Description

Figure 4.22 and Figure 4.23 show the comparison between stock realized volatility and that of oil and Euro-dollar foreign exchange respectively.

Comparison Within Asset Class

We now turn to statistical properties of asset volatilities within each asset class. Table 4.4 to Table 4.7 show the results for stock, gold, oil, and foreign exchange respectively.

[28] For more details on the methodology, the reader is referred to the website of the authors: https://www.policyuncertainty.com/methodology.html

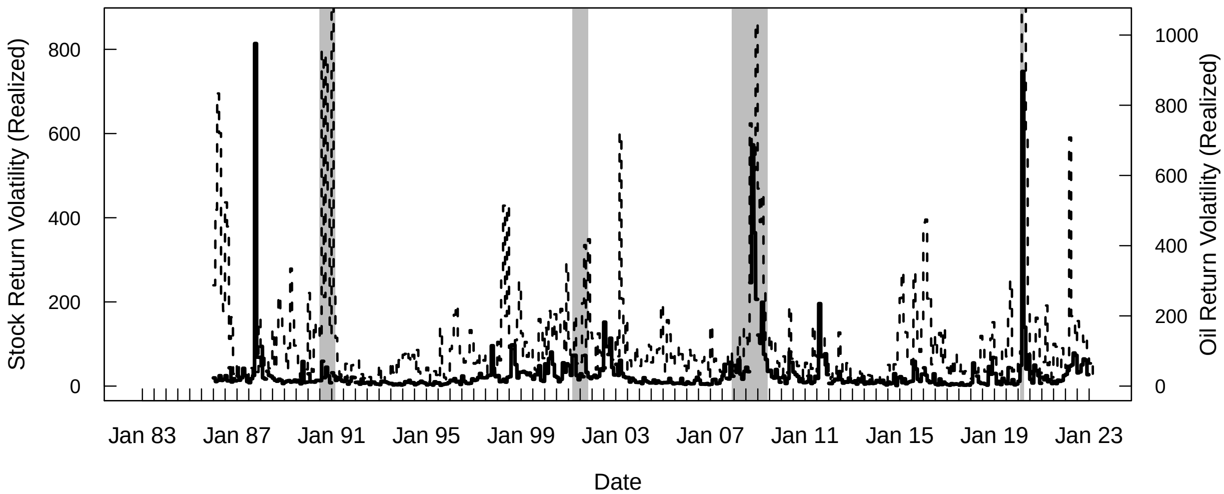

Figure 4.22: Asset Return Volatility: Stock vs. Oil.

Note: The solid line displays the realized volatility of the stock returns in the US, and the dash line the realized volatility of oil return volatility. Shaded regions denote the recession period. Note that to keep a reasonable perspective of comparison, we exclude three extreme high values of oil volatilities. The values are respectively 5499.732, 4743.401, and 2503.611. The first two happened during the Covid crisis and the last one during the Gulf War. Shaded regions denote the recession period.

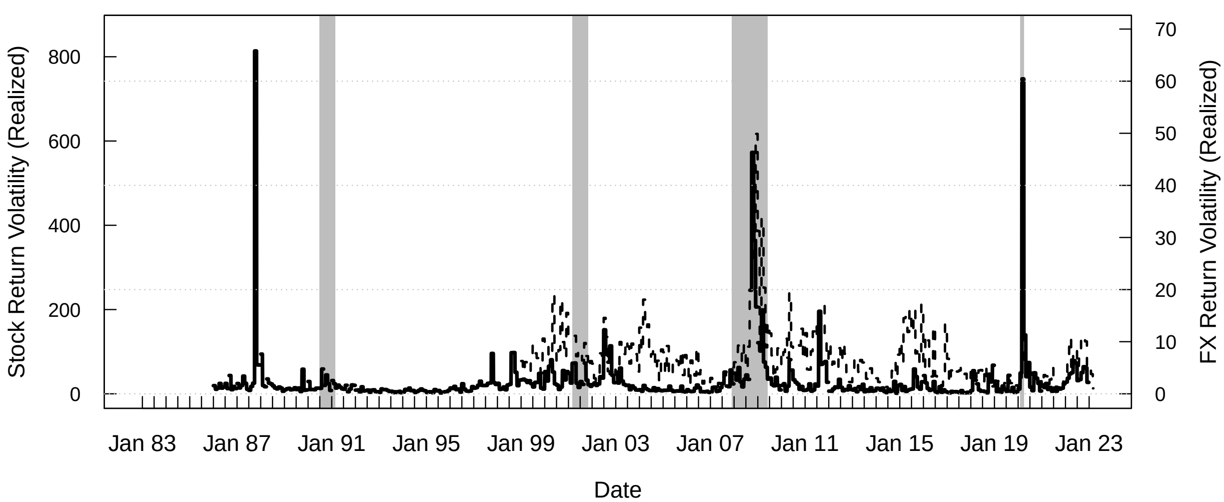

Figure 4.23: Asset Return Volatility: Stock vs. FX.

Note: The solid line displays the realized volatility of the stock returns in the US, and the dash line the realized volatility of Euro-dollar foreign exchange return volatility. Shaded regions denote the recession period.

Class	Variable	Realized Vol.	Implied Vol.
Equity	SP500	since 1990	since 1990
Oil	Oil	since 1990	since 2007
Gold	Gold	since 1990	since 2008
Foreign Exchange	Euro-Dollar	since 1999	since 2007

Table 4.3: Coverage of Asset Classes and Time Periods.

Note: The table shows the corresponding variable used for each asset class and their respective time period.

	Return	RV	IV
Return	1	-0.41	-0.19
RV		1	0.79
IV			1

	Return	RV	IV
Return	1	-0.49	-0.41
RV		1	0.84
IV			1

Table 4.4: Correlation of Stock Volatilities.

Note: The correlation table of stock daily returns, implied volatility and realized volatility. Time horizon for left table is 1990-2008. Time horizon for right table is 2008-2019.

	Return	RV
Return	1	0.10
RV		1

	Return	RV	IV
Return	1	-0.16	-0.03
RV		1	0.80
IV			1

Table 4.5: Correlation of Gold Volatilities.

Note: The correlation table of gold daily returns, implied volatility and realized volatility. Time horizon for left table is 1990-2008. Time horizon for right table is 2008-2019.

	Return	RV
Return	1	-0.01
RV		1

	Return	RV	IV
Return	1	-0.02	-0.07
RV		1	0.85
IV			1

Table 4.6: Correlation of EX Volatilities.

Note: The correlation table of Euro-Dollar exchange rate daily returns, implied volatility and realized volatility. Time horizon for left table is 1990-2008. Time horizon for right table is 2008-2019.

	Return	RV
Return	1	-0.16
RV		1

	Return	RV	IV
Return	1	-0.34	-0.27
RV		1	0.85
IV			1

Table 4.7: Correlation of Oil Volatilities.

Note: The correlation table of oil daily returns, implied volatility and realized volatility. Time horizon for left table is 1990-2008. Time horizon for right table is 2008-2019.

Comparing the result, we see that first, realized and implied volatility are positively correlated for all asset classes. This generalizes the finding in Berger et al. (2020) about stock prices to other asset classes such as oil, gold, and the Euro-Dollar exchange rate. This correlation clearly shows that realized, and expected volatilities are linked. However, it is hard to pin down if realized second-moment shocks make investors build expectations of future volatility or if news about future volatility makes investors trade assets heavily, driving up realized volatility. This is indeed a complex and exciting empirical question.

Second, returns are not correlated in most cases to either volatility, implied, or realized. This is most clear in the case of the Euro-Dollar exchange rate, where returns have almost zero correlation with each volatility. This is also the case for gold and oil prices.

Lastly, the second point holds the implied volatility of stock prices before 2008. However, it is noteworthy that realized volatility is negatively correlated with returns and has increased significantly post-2008 for implied volatility. In other words, an increase in volatility realized or implied (and they often come together) is associated with negative returns, on average. Future theoretical work should consider this asymmetric feature of the data.

Comparison Across Asset Class

First Order Moments We begin the analysis by examining how the first-order moments correlate across asset classes, namely the daily returns calculated as the log difference in asset prices. Table 4.8 shows that daily returns are not strongly correlated systematically across asset classes. In particular, gold and stock prices are not correlated, while oil and stock prices show the highest correlation among the asset class pairs. To a lesser extent, the returns on the US stock markets are positively correlated with the Euro-Dollar exchange rate.

	Stock	Gold	EUR	Oil
Stock	1	0.01	0.43	0.50
Gold		1	0.35	0.14
EUR			1	0.38
Oil				1

Table 4.8: Correlation of Returns.

Note: Correlation table across the daily returns of different asset classes: Stocks, Gold, Euro-Dollar exchange rate and oil. Time horizon: 2008 to 2019.

Second Order Moments We then turn to the second order moments, namely the two concepts defined in the previous section of realized and implied volatility, and map out how they co-move with respect to each other. The main take-away from tables (**??**) is that second-order moments are systematically more correlated across assets than first moments. In particular, the realized volatility of gold prices and stock prices have the highest correlation (0.78) while the realized volatility of gold prices and oil prices have the lowest but still high correlation (0.5). Further, implied volatility shows an even higher co-movement across asset classes, with the highest again between stock prices and gold prices (0.86) and the lowest between gold prices and oil prices (0.68). On the one hand, that returns are not as correlated as realized volatility across assets suggests that even if the drivers of first order returns diverge, what explains second order moment could be common across asset classes. Candidate drivers are aggregate uncertainty, investor sentiment, monetary policy, and risk appetite, among others. On the other hand, the higher correlation of implied volatility across asset classes points to the fact that the accuracy of agent's expectations about the future has an important common component, even if the realization of the second order moments is subject to idiosyncratic and asset specific shocks.

	Realized Volatility					Implied Volatility			
	Stock	Gold	EUR	Oil		Stock	Gold	EUR	Oil
Stock	1	0.78	0.69	0.68	Stock	1	0.86	0.83	0.77
Gold		1	0.55	0.50	Gold		1	0.81	0.68
EUR			1	0.74	EUR			1	0.73
Oil				1	Oil				1

Table 4.9: Correlation of RV and IV.

Note: Correlation table across the realized volatility (Left table) and the implied volatility (Right Table) of different asset classes: Stocks, Gold, Euro-Dollar exchange rate and oil. Time horizon: 2008 to 2019.

Principal Component Analysis

To capture the common component of the volatilities of different assets, we formalize the exercise of common versus idiosyncratic drivers of realized and implied volatility. To do this, we perform two separate principal component analysis: one on the realized volatilities of the four asset classes, and the other on their implied volatilities.

Assume that each volatility is represented using the following representation:

$$Vol_t^j = \sum_{i=1}^{4} \lambda^i PC_t^i \tag{4.6.1}$$

where Vol is respectively realized volatility (RV) or implied volatility (IV) of asset class j (stocks, gold, Euro-Dollar exchange rate and oil).

	Realized Volatility				Implied Volatility			
	PC_1^{RV}	PC_2^{RV}	PC_3^{RV}	PC_4^{RV}	PC_1^{IV}	PC_2^{IV}	PC_3^{IV}	PC_4^{IV}
Var share	0.63	0.21	0.11	0.03	0.75	0.14	0.06	0.03
Cumul. share	0.63	0.85	0.96	1	0.75	0.90	0.96	1

Table 4.10: Results of the two separate principal component analysis on the realized and implied volatilities respectively and applied on different asset classes: Stocks, Gold, Euro-Dollar exchange rate and oil. Time horizon: 2008 to 2019. The first row reports the percentage of the total variance explained by each principal component of realized and implied volatility and the second row is the cumulative of the first row shares respectively.

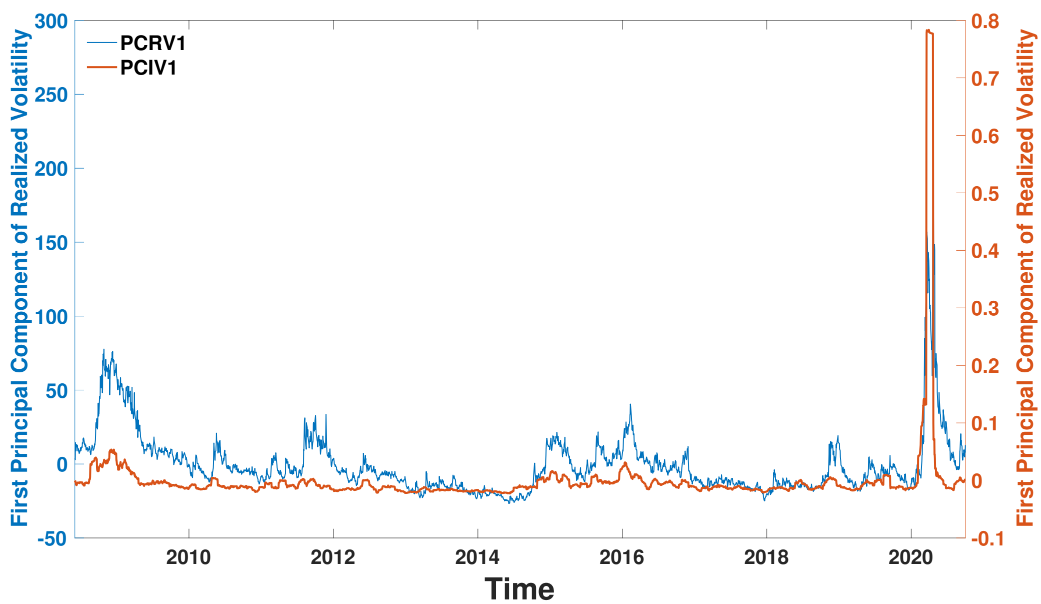

Figure 4.24: Graph of the time series of the first principal component (done in section **??**) of realized and implied volatilities across asset classes between 2008 and 2020. The correlation of these two factors is high (0.6).

Stock-Gold Comparison

It is interesting to note that gold price returns are not correlated with the second moments of stock prices, while stock price returns are negatively correlated with the second moments of gold prices. When the gold market experiences or expects volatility, this is usually associated with negative returns for the stock market.

	Stock IV	Stock RV	Gold IV	Gold RV
Stock return	-0.41	-0.49	-0.35	-0.41
Gold return	0.07	-0.04	-0.03	-0.16

Table 4.11: Correlation table of stock and gold prices return with respective implied and realized volatilities.

The core mechanism in Gabaix (2012) is consistent with our idea of separating the contribution of aggregate and asset specific risks to asset volatility, as the time-varying disaster probability is essentially a notion very similar to time-varying uncertainty. In addition, the author assumes that different stocks have different degree of *recovery* ability, indicating that some stock might be more *resistance* to change in aggregate conditions. In our context of multiple asset classes, one way to interpret our results is that gold is an asset that exhibit higher resistance to aggregate uncertainty. Therefore, future work could explore incorporating similar features, so as to detect a change in risk-aversion since it is better picked up by asset with high resistance to uncertainty.

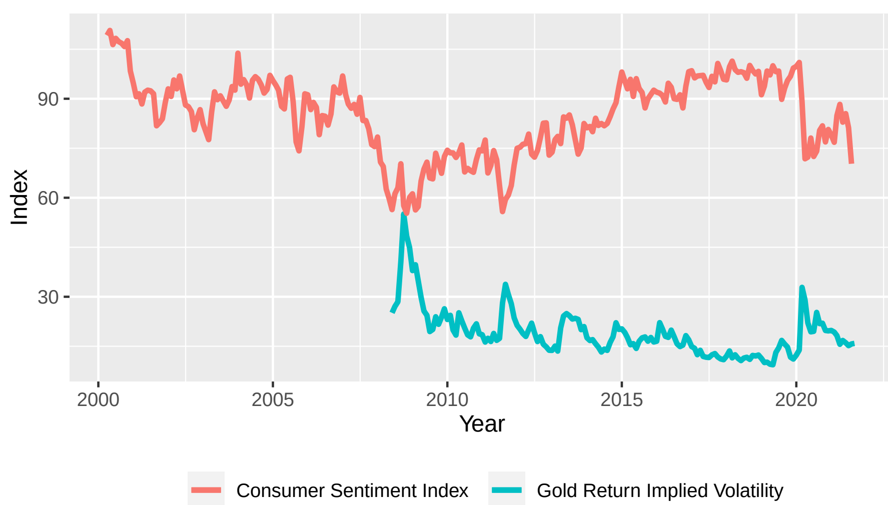

Figure 4.25: Gold Volatility vs. Sentiment

4.6.3 SVAR Analysis

Data Description

Macroeconomic data We use monthly economic data, following the literature (Bloom (2009); Leduc and Liu (2016)). This is appropriate given that fluctuations in either realized or implied volatility could be short-lived while still having important consequences. Moreover, this has the bonus of maximizing statistical power in our VARs. We include an index for real economic activity, price, and monetary policy index. For real activity, we use the index produced by the Board of Governors of the Federal Reserve System [29] of industrial production.[30] Additionally, we use the U.S. consumer price index[31] produced by the U.S. Bureau of Labor Statistics[32]and the Federal Fund Effective Rate[33], as controls and to avoid misspecification in the VAR. Both are downloaded from FRED.[34]

Table 4.12: Data Description

Variable	Data	Data Description
Output	GDPC1(ln)	Real Gross Domestic Product
	GDPC1 (FD)	RGDP first difference
Inflation	CPIAUCSL (ln)	Consumer Price Index for All Urban Consumers
	PCECTPI (ln)	Personal Consumption Expenditures
Unemployment	UNRATE	Unemployment rate
Monetary Policy	FEDFUNDS	Effective Federal Funds Rate
	DGS1	1-Year Treasury Constant Maturity Rate
	DGS2	2-Year Treasury Constant Maturity Rate
	Shadow Rate	Shadow interest rate by Wu and Xia (2016)
Sentiment	UMCSENT	Michigan consumer sentiment
	MICH	Michigan consumer inflation expectation
	EBP	Excess bond premium by Gilchrist and Zakrajšek (2012)
	SKEWNESS	CBOE Skewness index

[29] Board of Governors of the Federal Reserve System (U.S.), Industrial Production: Total Index [INDPRO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/INDPRO, August 20, 2022. For reference: Board of Governors of the Federal Reserve System. "Industrial Production and Capacity Utilization." Statistical release G.17; May 2013.

[30] "The Industrial Production Index (INDPRO) is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories)."

[31] "The Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL) is a price index of a basket of goods and services paid by urban consumers. "

[32] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in the U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, August 20, 2022.

[33] "The federal funds rate is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight."

[34] Board of Governors of the Federal Reserve System (U.S.), Federal Funds Effective Rate [DFF], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DFF, August 19, 2022.

Exogeneity Tests

Unrestricted VAR

$$\begin{aligned} RV_t &= \mathbf{b_{11}RV_{t-1}} + \mathbf{b_{12}IV_{t-1}} + \mathbb{B}_{13}\mathbf{y_{t-1}} + u_{1t} \\ IV_t &= \mathbf{b_{21}RV_{t-1}} + \mathbf{b_{22}IV_{t-1}} + \mathbb{B}_{23}\mathbf{y_{t-1}} + u_{2t} \\ \mathbf{y}_t &= \mathbf{B_1RV_{t-1}} + \mathbf{B_2IV_{t-1}} + \mathbf{B_3y_{t-1}} + \mathbf{u_t} \end{aligned} \tag{4.6.2}$$

where $\mathbf{RV_{t-1}} = (RV_{t-1}, RV_{t-2}, ..., RV_{t-p})'$ is a $p \times 1$ vector of lagged values of realized volatility. $\mathbf{b_{11}}$ and $\mathbf{b_{21}}$ are two $1 \times p$ vectors of coefficients to these lagged values. $\mathbf{IV_{t-1}}$, together with the coefficients $\mathbf{b_{12}}$ and $\mathbf{b_{22}}$ is defined in similar fashion. $\mathbf{y}_t$ is a vector that contains all the other endogenous variables, and $\mathbf{B_3}$ and $\mathbf{y_{t-1}}$ are the respective coefficient matrix and the lagged values.

- Null hypothesis: $\mathbb{B}_{13} = \mathbb{B}_{23} = 0$.
- Interpretation: The restrictions on the regression coefficients before realized and implied volatilities are affected only by their own lags, not the lags of other variables.

Restricted VAR

$$\begin{aligned} RV_t &= \mathbf{b_{11}RV_{t-1}} + \mathbf{b_{12}IV_{t-1}} + u_{1t} \\ IV_t &= \mathbf{b_{21}RV_{t-1}} + \mathbf{b_{22}IV_{t-1}} + u_{2t} \\ \mathbf{y}_t &= \mathbf{B_1RV_{t-1}} + \mathbf{B_2IV_{t-1}} + \mathbf{B_3y_{t-1}} + \mathbf{u_t} \end{aligned} \tag{4.6.3}$$

- Test: χ^2 test on the joint distribution of the estimated coefficients.

Results

	1992 - 2000	2002-2007	2010-2019
Stocks	0.0108	0.0000	0.6290
Gold			0.0165
Euro-Dollar			0.0407
Oil			0.2041

- For stocks prices, in the sample period from 1992 to 2000 and 2002 to 2007, the p-value is below 5%. This is robust to the variation of the ending date of the sub-sample as the value is always below 5% whether we stop at 2007 or 2009. This means that the assumption that stock volatilities are not affected by lagged economic variables are strongly rejected. Both realized and implied volatilities of stock prices are more likely to be endogenous to macroeconomic variables.

- In the sample period from 2010 to 2019, the p-value is much higher. This implies that the assumption that the coefficients of the lagged economic variables equal zero cannot be rejected. In this later sample, realized and implied volatilities of stock prices are more likely to be exoegnous to macroeconomics variables.
- The results are robust to changing lagged explanatory variables into leads, indicating that the result is not due to the fact that volatilities may contain forward-looking information.

For other assets, the processes of implied volatility start after 2008. So we only have the 2010-2019 sample.

- For gold prices, the p-value is below 5%, suggesting that the null hypothesis is strongly rejected. The result is robust to changing the lagged variables into leads. Both realized and implied volatilities of gold prices are more likely to be endogenous to macroeconomic variables.
- For the Euro-Dollar exchange rate, the p-value is slightly below 5%, so the assumption cannot be rejected. But using leads of the variables instead of lags yields a lower p-value, suggesting that the exchange rate volatilities might be containing more forwarding looking components, which are more likely to be endogenous to macroeconomic variables.
- For oil prices, the p-value is above 5%. The null of exogeneity is not rejected. However, using leads of the variables instead of lags yields a much lower p-value, suggesting that the oil volatilities might be containing more forwarding looking components, which are more likely to be endogenous to macroeconomic variables.

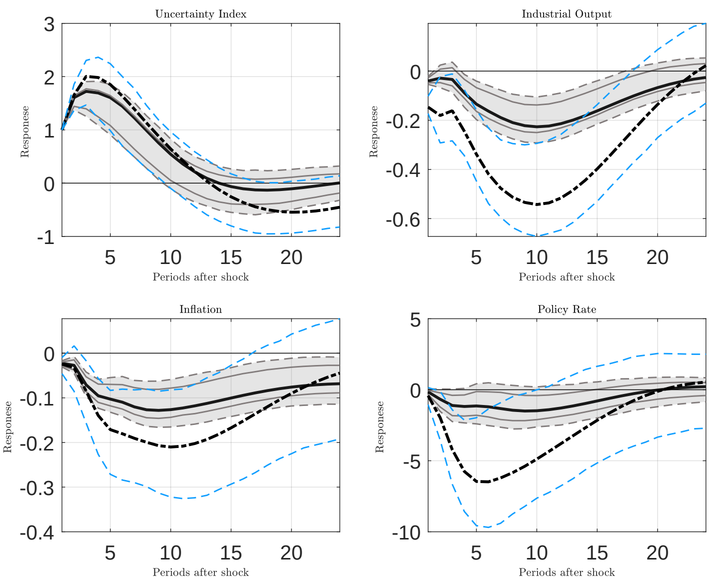

Figure 4.26: IRF to Uncertainty Shock (2008-2019)

Note: The figure shows the IRFs to identified uncertainty shock using Financial Uncertainty Index (solid line) and Macro Uncertainty Index (dashed line) from Jurado et al. (2015). Sample is from 2008 to 2019. The shaded area shows [16, 86] and [5, 95] percent confidence interval for the uncertainty shock using financial uncertainty index.

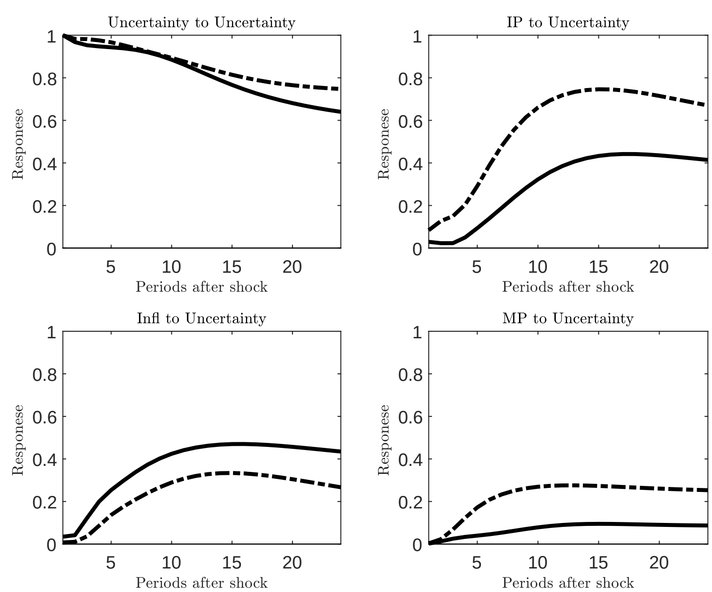

Figure 4.27: IRF to Uncertainty Shock (2008-2019)

Note: The figure shows the FEVDs to identified uncertainty shock using Financial Uncertainty Index (solid line) and Macro Uncertainty Index (dashed line) from Jurado et al. (2015).

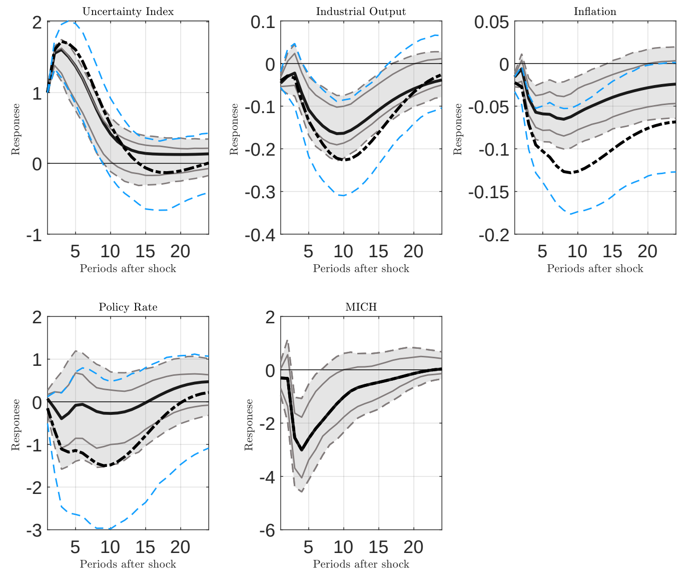

Figure 4.28: IRF to Uncertainty Shock (2008-2020)

Note: The figure shows the IRFs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and without Michigan Consumer Index (dashed line). Sample is from 2008 to 2020. The shaded area shows [16, 86] and [5, 95] percent confidence interval for the uncertainty shock using financial uncertainty index.

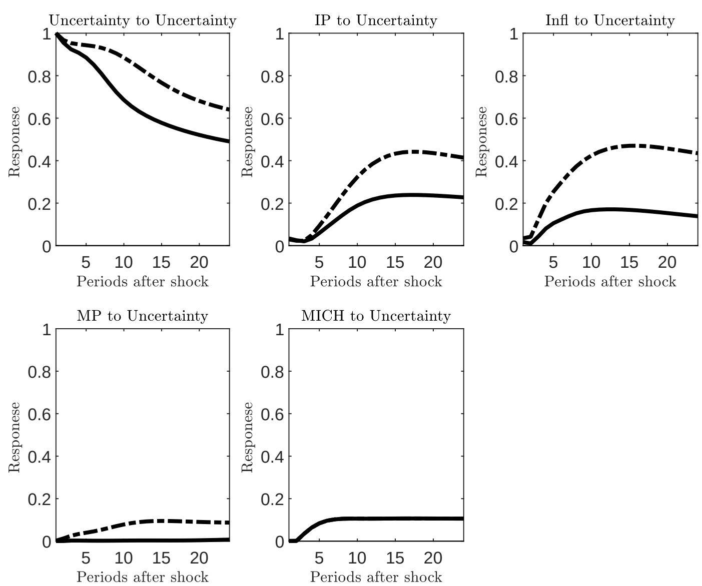

Figure 4.29: IRF to Uncertainty Shock (2008-2020)

Note: The figure shows the FEVDs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and without Michigan Consumer Index (dashed line).

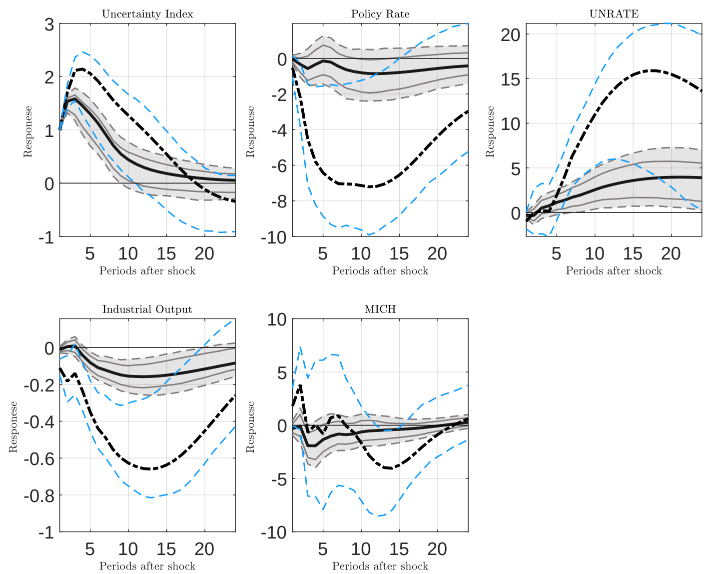

Figure 4.30: IRF to Uncertainty Shock (2008-2020)

Note: The figure shows the IRFs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and Macro Uncertainty Index (dashed line). Sample is from 2008 to 2020. The shaded area shows [16, 86] and [5, 95] percent confidence interval for the uncertainty shock using financial uncertainty index.

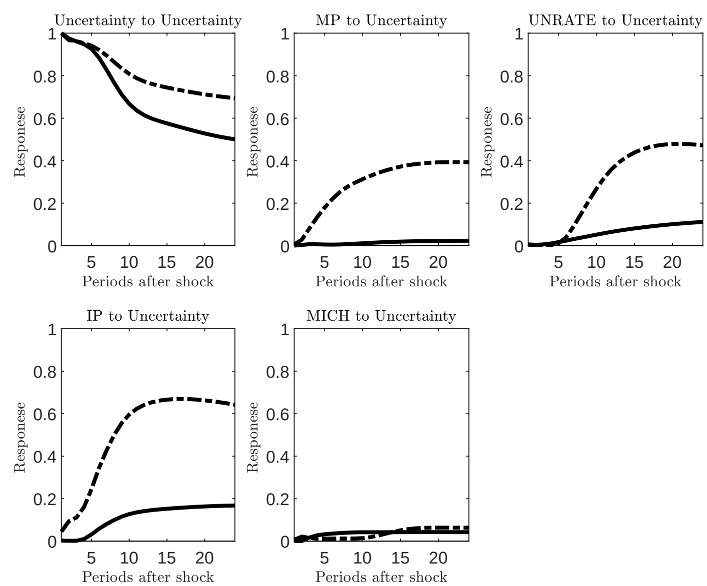

Figure 4.31: IRF to Uncertainty Shock (2008-2020)

Note: The figure shows the FEVDs to identified uncertainty shock using Financial Uncertainty Index with (solid line) and without Michigan Consumer Index.

Baseline Identification

Identification à la BDG

4.6.4 Theoretical Model

Solution to the Toy Model

We first compute the optimal asset holding

$$s_i = \frac{\mathbb{E}_i[(1-\gamma)d] - q + u + v_i}{\gamma(1+\bar{Q}/\bar{L})} + \frac{\mathbb{E}_i\left[l_i\right]}{1+\bar{Q}/\bar{L}}$$

Given the optimal asset holding, the agents need to guess the values of $\mathbb{E}_i[(1-\gamma)d]$ and $\mathbb{E}_i\left[l_i\right]$, which requires the inference of ε_a and ε_l from the exogenous signal $x = \varepsilon_a + \varepsilon_l$ and the endogenous signal q

$$\begin{aligned} q =& q_a\varepsilon_a + q_l\varepsilon_l + q_u u \\ \hat{q} =& \varepsilon_a + (q_l/q_a)\varepsilon_l + (q_u/q_a)u = \varepsilon_a + \hat{\varepsilon}_l + \hat{u} \end{aligned}$$

Applying Gaussian Projection Theorem, we have

$$\begin{aligned} \tau_q =& \frac{\frac{1}{g_l^2\sigma_l^2} + \frac{1}{g_u^2\sigma_u^2}}{\frac{1}{\sigma_a^2} + \frac{1}{\sigma_l^2} + \frac{1}{g_l^2\sigma_l^2} + \frac{1}{g_u^2\sigma_u^2}} = \frac{g_u^2\sigma_a^2\sigma_l^2\sigma_u^2 + g_l^2\sigma_a^2\sigma_l^2\sigma_l^2}{g_u^2g_l^2\sigma_a^2\sigma_u^2\sigma_l^2 + g_u^2g_l^2\sigma_l^2\sigma_u^2\sigma_l^2 + g_l^2\sigma_a^2\sigma_l^2\sigma_l^2 + g_u^2\sigma_a^2\sigma_l^2\sigma_u^2} \in (0,1) \\ =& \frac{g_u^2\sigma_a^2\sigma_u^2 + g_l^2\sigma_a^2\sigma_l^2}{g_u^2g_l^2\sigma_l^2\sigma_u^2 + g_l^2\sigma_a^2\sigma_l^2 + (g_l^2+1)g_u^2\sigma_a^2\sigma_u^2} \\ \tau_x =& \frac{\frac{1}{\sigma_l^2}}{\frac{1}{\sigma_a^2} + \frac{1}{\sigma_l^2} + \frac{1}{g_l^2\sigma_l^2} + \frac{1}{g_u^2\sigma_u^2}} = \frac{g_l^2g_u^2\sigma_a^2\sigma_l^2\sigma_u^2}{g_u^2g_l^2\sigma_a^2\sigma_u^2\sigma_l^2 + g_u^2g_l^2\sigma_l^2\sigma_u^2\sigma_l^2 + g_l^2\sigma_a^2\sigma_l^2\sigma_l^2 + g_u^2\sigma_a^2\sigma_l^2\sigma_u^2} \in (0,1) \\ =& \frac{g_l^2g_u^2\sigma_a^2\sigma_u^2}{g_u^2g_l^2\sigma_l^2\sigma_u^2 + g_l^2\sigma_a^2\sigma_l^2 + (g_l^2+1)g_u^2\sigma_a^2\sigma_u^2} \end{aligned}$$

where $g_u = q_u/q_a$ and $g_l = q_l/q_a$.

$$\begin{aligned} \overline{\mathbb{E}}[d] = \mathbb{E}_i[d] =& x_d\left(\tau_q\hat{q} + \tau_x x_i\right) + \kappa x_l\left(-\tau_q\hat{q} + (1-\tau_x)\,x\right) \\ =& \left(x_d\tau_q - \kappa x_l\tau_q\right)\hat{q} + \left(x_d\tau_x + \kappa x_l\left(1-\tau_x\right)\right)x \\ \overline{\mathbb{E}}[l_i] = \mathbb{E}_i\left[l_i\right] =& x_l\left(-\tau_q\hat{q} + (1-\tau_x)\,x\right) \\ =& -x_l\tau_q\hat{q} + x_l\left(1-\tau_x\right)x \end{aligned} \tag{4.6.4}$$

Taking these expectations back to the price equation yields

$$\begin{aligned} q =& (1-\gamma)\overline{\mathbb{E}}[d] + \gamma\overline{\mathbb{E}}\left[l_i\right] + u \\ =& (1-\gamma)\left[\left(x_d\tau_q - \kappa x_l\tau_q\right)\hat{q} + \left(x_d\tau_x + \kappa x_l\left(1-\tau_x\right)\right)x\right] + \gamma\left[-x_l\tau_q\hat{q} + x_l\left(1-\tau_x\right)x\right] + u \end{aligned}$$

Collecting the terms yields

$$\begin{aligned} q &= \left[(1-\gamma)\left(x_d\tau_q - \kappa x_l\tau_q\right) - \gamma x_l\tau_q\right]\hat{q} + \left[(1-\gamma)\left(x_d\tau_x + \kappa x_l\left(1-\tau_x\right)\right) + \gamma x_l\left(1-\tau_x\right)\right]x + u \\ &= \left[(1-\gamma)x_d\tau_q - (1-\gamma)\kappa x_l\tau_q - \gamma x_l\tau_q\right]\hat{q} + \left[(1-\gamma)x_d\tau_x + (1-\gamma)\kappa x_l\left(1-\tau_x\right) + \gamma x_l\left(1-\tau_x\right)\right]x + u \\ &= \left[(1-\gamma)x_d\tau_q - \left((1-\gamma)\kappa + \gamma\right)x_l\tau_q\right]\hat{q} + \left[(1-\gamma)x_d\tau_x + \left((1-\gamma)\kappa x_l + \gamma\right)x_l\left(1-\tau_x\right)\right]x + u \end{aligned}$$

Expanding the expression for $\hat{q}$ and x yields

$$\begin{aligned} q = & \left[(1-\gamma)x_d\tau_a + \left((1-\gamma)\kappa + \gamma\right)x_l\tau_i\right]\varepsilon_a \\ & + \left[(1-\gamma)g_u\tau_q x_d - \left((1-\gamma)\kappa + \gamma\right)g_u\tau_q x_l + 1\right]u \\ & + \left[(1-\gamma)x_d\tilde{\tau}_a + \left((1-\gamma)\kappa + \gamma\right)x_l\tilde{\tau}_i\right]\varepsilon_l \end{aligned}$$

where $\tau_a = \tau_q + \tau_x \in (0,1)$ $\tau_i = 1 - \left(\tau_q + \tau_x\right)$, $\tilde{\tau}_a = g_l\tau_q + \tau_x$, and $\tilde{\tau}_i = 1 - \left(g_l\tau_q + \tau_x\right)$. Matching coefficients yield

$$\begin{aligned} q_a &= \left[(1-\gamma)x_d\tau_a + \left((1-\gamma)\kappa + \gamma\right)x_l\tau_i\right] \\ q_l &= \left[(1-\gamma)x_d\tilde{\tau}_a + \left((1-\gamma)\kappa + \gamma\right)x_l\tilde{\tau}_i\right] \\ q_u &= \left[(1-\gamma)g_u\tau_q x_d - \left((1-\gamma)\kappa + \gamma\right)g_u\tau_q x_l + 1\right] \end{aligned}$$

which pin down the coefficients guessed.

Asset-specific Uncertainty

In this simplified case, we omit from the homogeneous component in the expectation deviation, u. Therefore, the guess for the price becomes

$$\begin{aligned} q =& q_a\varepsilon_a + q_l\varepsilon_l \\ \hat{q} =& \varepsilon_a + (q_l/q_a)\varepsilon_l = \varepsilon_a + \hat{\varepsilon}_l \end{aligned}$$

Applying Gaussian Projection Theorem, we have

$$\tau_q = \frac{\frac{1}{g_l^2\sigma_l^2}}{\frac{1}{\sigma_a^2}+\frac{1}{\sigma_l^2}+\frac{1}{g_l^2\sigma_l^2}} = \frac{\sigma_a^2\sigma_l^2}{g_l^2\sigma_l^2\sigma_l^2+g_l^2\sigma_a^2\sigma_l^2+\sigma_a^2\sigma_l^2} = \frac{\sigma_a^2}{g_l^2\sigma_l^2+g_l^2\sigma_a^2+\sigma_a^2}$$

$$\tau_x = \frac{\frac{1}{\sigma_l^2}}{\frac{1}{\sigma_a^2}+\frac{1}{\sigma_l^2}+\frac{1}{g_l^2\sigma_l^2}} = \frac{g_l^2\sigma_a^2\sigma_u^2}{g_l^2\sigma_l^2\sigma_l^2+g_l^2\sigma_a^2\sigma_l^2+\sigma_a^2\sigma_l^2} = \frac{g_l^2\sigma_a^2}{g_l^2\sigma_l^2+g_l^2\sigma_a^2+\sigma_a^2}$$

where $g_l = q_l/q_a$. Since we have

$$\begin{aligned} q =&(1-\gamma)\overline{\mathbb{E}}[d]+\gamma\overline{\mathbb{E}}\left[l_i\right] \\ =&\left[(1-\gamma)x_d\tau_q-((1-\gamma)\kappa+\gamma)\,x_l\tau_q\right]\hat{q}+\left[(1-\gamma)x_d\tau_x+((1-\gamma)\kappa x_l+\gamma)\,x_l\,(1-\tau_x)\right]x \\ =&\left[(1-\gamma)x_d\tau_a+((1-\gamma)\kappa+\gamma)\,x_l\tau_i\right]\varepsilon_a+\left[(1-\gamma)x_d\tilde{\tau}_a+((1-\gamma)\kappa+\gamma)\,x_l\tilde{\tau}_i\right]\varepsilon_l \end{aligned}$$

where $\tau_a = \tau_q+\tau_x \in (0,1)$ $\tau_i = 1-\left(\tau_q+\tau_x\right)$, $\tilde{\tau}_a = g_l\tau_q+\tau_x$, and $\tilde{\tau}_i = 1-\left(g_l\tau_q+\tau_x\right)$. Matching coefficients yield

$$\begin{aligned} q_a =&\left[(1-\gamma)x_d\tau_a+((1-\gamma)\kappa+\gamma)\,x_l\tau_i\right] \\ q_l =&\left[(1-\gamma)x_d\tilde{\tau}_a+((1-\gamma)\kappa+\gamma)\,x_l\tilde{\tau}_i\right] \\ g_l =&\frac{q_l}{q_a} = \frac{\left[(1-\gamma)x_d\tilde{\tau}_a+((1-\gamma)\kappa+\gamma)\,x_l\tilde{\tau}_i\right]}{\left[(1-\gamma)x_d\tau_a+((1-\gamma)\kappa+\gamma)\,x_l\tau_i\right]} \end{aligned}$$

which pin down the coefficients guessed.

$$\begin{aligned} g_l =&\frac{\left[(1-\gamma)x_d(g_l\tau_q+\tau_x)+((1-\gamma)\kappa+\gamma)\,x_l(1-(g_l\tau_q+\tau_x))\right]}{\left[(1-\gamma)x_d(\tau_q+\tau_x)+((1-\gamma)\kappa+\gamma)\,x_l(1-(\tau_q+\tau_x))\right]} \\ =&\frac{\left[(1-\gamma)x_d(g_l+g_l^2)\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_l(g_l^2\sigma_l^2+\sigma_a^2-g_l\sigma_a^2)\right]}{\left[(1-\gamma)x_d(1+g_l^2)\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_lg_l^2\sigma_l^2\right]} \end{aligned}$$

Matching coefficients yields a cubic equation for g_l:

$$\begin{aligned} 0 =&\left[(1-\gamma)x_d\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_l\sigma_l^2\right]g^3-\left[(1-\gamma)x_d\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_l\sigma_l^2\right]g^2 \\ &+((1-\gamma)\kappa+\gamma)\,x_l\sigma_a^2g-((1-\gamma)\kappa+\gamma)\,x_l\sigma_a^2 \\ 0 =&\left[(1-\gamma)x_d\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_l\sigma_l^2\right](g^3-g^2)+((1-\gamma)\kappa+\gamma)\,x_l\sigma_a^2(g-1) \end{aligned}$$

If $g \neq 1$, the above expression can be reduced to

$$0 = \left[(1-\gamma)x_d\sigma_a^2+((1-\gamma)\kappa+\gamma)\,x_l\sigma_l^2\right](g^2-g)+((1-\gamma)\kappa+\gamma)\,x_l\sigma_a^2$$

Therefore, we have

$$g = \frac{\mathcal{A} \pm (\mathcal{A}^2 - 4\mathcal{A}\mathcal{B})^{1/2}}{2\mathcal{A}}$$

where $\mathcal{A} = \left[(1-\gamma)x_d\sigma_a^2 + ((1-\gamma)\kappa + \gamma)\, x_l\sigma_l^2\right]$ and $\mathcal{B} = ((1-\gamma)\kappa + \gamma)\, x_l\sigma_a^2$.

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