THÈSE

En vue de l'obtention du

DOCTORAT DE L'UNIVERSITE DE TOULOUSE

Délivré par l'Université Toulouse Capitole

École doctorale : **Sciences Economiques-Toulouse School of Economics**

Présentée et soutenue par

PIETRUNTI Mario

le 29 juin 2016

Essays in Applied Macroeconomics

Discipline : **Sciences Economiques**

Unité de recherche : **TSE-R (UMR CNRS 5314 – INRA 1415)**

Directeur de thèse : Monsieur Patrick FEVE Professeur Université Toulouse 1 Capitole

JURY

Rapporteurs Monsieur Franck PORTIER Professeur Université Toulouse 1 Capitole
Monsieur Christian HELLWIG Professeur Université Toulouse 1 Capitole

Suffragants Monsieur Fabrice COLLARD Professeur Université de Bern
Monsieur Guido LORENZONI Professeur Université de Northwestern
Monsieur Martial DUPAIGNE Professeur Université de Montpellier 3

Acknowledgments

This thesis would not have been possible without the support of many people.

Patrick Fève has been an invaluable source of inspiration and encouragement and I deem myself lucky to have had him as my main advisor. I am grateful for his constant advice and for the long and instructive conversations we had.

I am also indebted to Roberto Pancrazi for his generous advice and support throughout the years.

When in Toulouse, I had useful discussions and guidance from people in the macro group and especially from Christian Hellwig.

Part of the thesis has been written while working at Banca d'Italia where I significantly benefited from discussions with many colleagues. I am particularly indebted to Paolo Angelini and to Stefano Neri for encouraging me at various stages of this long journey.

The three chapters of this thesis benefited from comments and discussions with Piergiorgio Alessandri, Philippe Andrade, Francesco Bianchi, Vincenzo Cuciniello, Davide Delle Monache, David Laibson, Eric Leeper, Matthieu Lemoine, Guido Lorenzoni, Julien Matheron, Leonardo Melosi, Eric Mengus, Karel Mertens, Fabrizio Perri, Giuseppe Ragusa, Valerie Ramey, Morten Ravn, Jean-Guillaume Sahuc, Stephanie Schmitt-Grohe, Anatoli Segura, Federico Signoretti and Javier Suarez.

I also gratefully acknowledge the kind hospitality of the Monetary Policy Research Division at Banque the France and of EIEF where I have been working on parts of this thesis.

Finally, I will be forever indebted to Marika for her endless support and to my parents and to Mary for their encouragement and understanding through the many years of research.

The research leading to Chapter 1 has received financial support from the European Research Council under the European Community's Seventh

Framework Program FP7/2007-2013 grant agreement N.263790. For Chapter 2 funding from ANR-13-BSH1-0002-AMF is gratefully acknowledged.

The views expressed herein are those of the author and should under no circumstances be interpreted as reflecting those of Banca d'Italia or the Eurosystem.

Abstract

This thesis investigates three different issues in applied macroeconomics.

In the first chapter (co-authored with Roberto Pancrazi) we document that long-run expectations of both households and, especially, financial intermediaries about future housing prices had a large impact on households' home equity extraction during the pre-crisis boom in U.S. housing prices. Using a model of collateralized credit market populated by households and banks we find that: (1) mild variations in long-run forecasts of housing prices result in quantitatively considerable differences in the amount of home equity extracted during the boom; (2) the equilibrium levels of debt and interest rate are particularly sensitive to financial intermediaries' expectations.

In the second chapter (co-authored with Patrick Fève), we investigate the macroeconomic effects of fiscal policy in a setting in which private agents receive noisy signals about future shocks to government expenditures. We show how to empirically identify the relative weight of news and noise shocks to government spending and compute the level of noise for Canada, the UK and the US. Embedding imperfect fiscal policy information in a medium-scale DSGE model, we find that with a persistent change in expected public spending, the existence of noise (as estimated using actual data) implies a sizable difference in fiscal multipliers compared to the perfect fiscal foresight case.

The third chapter studies the impact on the real economy of frictions stemming from the financial sector. First a non-linear medium scale DSGE with real and nominal rigidities is solved, where the non-linearity is induced by an occasionally binding constraint on banks' capital. Then likelihood-free methods are used to estimate the model on Italian data from 1999 to 2014. A key result is that the non-linear the model is able to generate business cycle asymmetries observed in actual data that cannot replicated with linear models. The model is then used for testing the usefulness of various macro-prudential policies, finding that taxing banks' leverage proves to be rather effective in smoothing the volatility of real variables, although there is no one-size-fits all policy, as each of them has a different impact on various features of the business cycle.

Contents

Introduction

After the Great Financial Crisis of 2008 the founding paradigms of modern macroeconomics have been significantly questioned both from within the profession and in the public opinion. On the one hand, it has been forcefully argued that the New-Keynesian DSGE orthodoxy was not adequately equipped for explaining episodes of crisis such as the one that followed the Lehman collapse or the one surrounding the sovereign debt crisis in the eurozone in 2011-2012. Therefore, a more accurate investigation of the mechanics of the financial sector and of the financial side of the economy has been praised. On the other hand, the role of informational frictions came more and more at the centre stage along with the study of limits in the ability of processing information on behalf of economic agents and the impact of partial information on business cycle dynamics. These essays span different subjects, while sharing a willingness to go beyond the pre-crisis paradigm, trying to embed both aspects. In the first two chapters the role of imperfect information and of biases in processing information is highlighted in two different contexts. The last one is an attempt to highlight the role of the financial sector on the business cycle and the relevance of endogenously induced asymmetries.

Natural Expectations and Home Equity Extraction In the first chapter (coauthored with Roberto Pancrazi) we propose a novel explanation for the increase in households' leverage during a housing price boom in which a wide availability of financial instruments allows agents to borrow today against the future *expected* value of their houses. We show that long-run expectations about future house prices of both households and, especially, financial intermediaries have a large impact on households' indebtedness. We are interested in assessing how the behavior of agents in the credit market is affected by *natural* expectations - that is, the tendency to base forecasts on simplified models that fail to take into account the long-run mean reversion of house prices after a positive short-run momentum.

The assumption that households behave in line with the *natural* expectations theory when confronting house prices is largely supported by empirical work. One novelty of this paper is its insight in documenting that financial experts also had *natural* expectations when they made their housing price forecasts - in the sense that they, too, ignored any form of long-run mean reversion in housing prices after the positive and strong short-run momentum. Specifically, we gather a unique dataset of out-of-sample housing price forecasts made by a professional forecasting company in the period 1995-2011 and show that these forecasts do not display any sort of adjustment after a period of short-run positive momentum: forecasts made prior to 2006 predict constant and large increases in long-run housing price until 2030. Then, we show that housing prices are characterized by hump-shaped dynamics, which imply a large momentum in the short run and partial mean reversion in the long run. We find that models that incorporate hump-shaped dynamics are not preferred, in terms of in-sample fit, to more parsimonious models that ignore long-run mean reversion. As a result, the use of simple models leading to natural beliefs is fully justifiable in terms of in-sample performance. Finally, we demonstrate that models that have diverse degrees of ability to capture hump-shaped dynamics in housing price market may differ in their long-run forecasts, while leading to similar short-run predictions. Hence, agents that make use of simple models fail to take into account the partial mean reversion of housing prices in the long run. Then, using a tractable model of a collateralized credit market populated by households and banks and calibrated to the recent house price boom-bust episode, we find that: (1) mild variations in long-run housing price forecasts result in quantitatively considerable differences in the amount of home equity extracted during a boom; (2) home equity extraction data are better matched by models in which agents are fairly *natural*; (3) the equilibrium level of debt and its interest rate are particularly sensitive to financial intermediaries' *naturalness*.

Noisy Fiscal Policy In Chapter 2 (co-authored with Patrick Fève) we extend the conventional framework of news shocks in fiscal policy considering an environment with imperfect information on fiscal policy. Given the considerable uncertainty surrounding the implementation of fiscal policy, it seems natural to extend the setup to imperfect information about news to the case of government spending. We thus focus on the macroeconomic effects of noisy fiscal policy announcements. By noisy announcements, we mean the following: A policymaker announces a fiscal policy measure at a particular point in time that is supposed to come into effect at a future date, while private agents in the economy believe that the announcement may not be fully implemented. Partial implementation may be due to amendments that occur during the legislative process or to incomplete information about future states of the economy. As a consequence, the information structure we examine is different from previous papers in which future fiscal policy is fully predictable. Thus, the main contribution is twofold: i) we quantify the size of noisy news using data from both forecasts and realizations of government spending; ii) we assess the effect of noise and its propagation through the economy using a medium-scale DSGE model with real frictions. The main result of this paper is that a "noisy" announcement leads to an under-reaction of macroeconomic variables to the announcement itself. The values of the fiscal multipliers drastically fall compared to the full information case. We make use of the official government spending forecasts from the annual budgets of three countries (Canada, the United Kingdom and the United States) for which we were able to obtain enough information. We find that the amount of noise observed for these three countries is rather significant: the share of noise in these official government spending forecasts ranges from 28% in the US to 84% in the UK. When embedding these estimates into a full-fledged DSGE model, we find that in a "noisy" scenario, before news events are realized, the value of government spending multipliers, compared to the full information case, falls proportionally to the level of noise. Additionally, the effect of noise does not vanish with the occurrence of the fiscal shock. For example, in the UK, for which the relevance of noise is most compelling, we obtain a loss in the output multiplier of approximately 10% one year after the materialization of the news compared to the perfect information case. Such an effect is more pronounced for investment, even in economies in which the role of noise is limited; for example, for the US, which is the country with the lowest share of noise among those considered, we find that the loss in the investment multiplier one year after the realization of a news event remains at approximately 12%, a non-negligible figure.

Financial Frictions, Macroprudential Policies and the Real Economy In Chapter 3, I attempt at quantitatively gauging the asymmetric impact on the real economy of financial frictions and at estimating the effectiveness of several macroprudential policies. Their widespread adoption notwithstanding, surprisingly little quantitative research has been performed so far on the effects of such policies on the real economy. The key research questions of the paper are then related to identify the impact on real variables of tensions arising in the banking sector and to investigate whether the timely implementation of macroprudential policies would have helped in mitigating the real effects of financial crises. In other words, I question whether there exist a one-size-fits-all macroprudential tool for dealing with financial crises.

I try and answer the above questions by making use of a DSGE model with a banking sector where financial frictions can bite only occasionally. This non-linearity within the banking sector should help in principle in identifying asymmetries in the cycle. It will also help in investigating the behavior of macroprudential policies in a non-linear environment. A further contribution of the paper is technical and is related to the estimation of large non-linear DSGE models. The model I am dealing with has indeed an occasionally binding constraint related to financial frictions in the economy; this implies that the model operates under two regimes: one in which financial frictions are in place and the other in which the allocation of resources is not affected by financial constraints. Such non-linearity is introduced to better capture the interaction between the financial system and the real economy. However, so far one of the main hurdles for investigating large non-linear models has been their computational complexity. Here I rely on a method recently brought forward in Guerrieri and Iacoviello (2015) for solving this class of models. One of the advantages of this method lies in its computational simplicity, which makes it possible to bring a medium scale model to the data. I therefore introduce a new estimation technique for DSGE models that does not rely on the estimation of the likelihood function. This method, that is gaining popularity in other disciplines, is known as Approximate Bayesian Computation (ABC, see Beaumont et al. 2002). I show that ABC can be easily implemented for estimating non-linear DSGE models and it provides several advantages compared to other methods currently used in the estimation of non-linear DSGE models, such as the Simulated Method of Moments. I show that the non-linear model is better able than linear models to approximate the asymmetries that can be observed in the data. More precisely, the estimated model accurately replicates the negative skewness of output and it better matches higher order moments (such as skewness and kurtosis) of output, consumption and investment.

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Chapter 1

Natural Expectations and Home Equity Extraction

1.1 Introduction

From 1999 to the end of 2006, U.S. household debt relative to income grew sharply, from 64 percent to more than 100 percent.[1] The increase in debt was accompanied by a sharp appreciation in housing prices: the Standard & Poor's Case-Shiller Home Price Index soared by 65 per cent in real terms in the same time span. Unlike previous episodes of heated housing markets, this housing price boom has been characterized by a surge in households' home equity extraction (HEE), through cash-out refinancing of mortgages, second lien home equity loans, or home equity lines of credit (henceforth, HELOCs). In 1992 the value of HEE was about $41 billion (in 2006 dollars); at the end of 1999, it more than doubled to about $95 billion; and from 2000 to 2006, when housing price growth was at its peak, HEE almost tripled (Figure 1.1).[2] Also, Greenspan and Kennedy (2005) document that households' gross home equity extraction as a fraction of disposable income increased from less than 3 percent to about 10 percent between 1997 and 2005.[3]

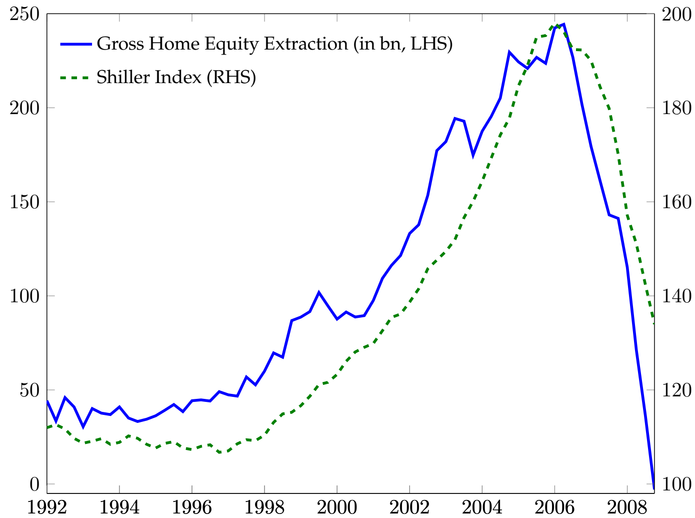
In this paper we propose a novel explanation for the increase in households' leverage during a housing price boom in which a wide availability of financial instruments allows agents to borrow today against the future

[1]Source: US. Bureau of Economic Analysis (GDP, BEA Account Code: A191RC1) and Federal Reserve System, Flow of Funds (Households and nonprofit organizations; total mortgages; liability, id: Z1/Z1/FL153165005.Q).

[2]Source: Federal Reserve System, Flow of Funds.

[3]Other works that have examined the role of home equity-based borrowing include Mian and Sufi (2011), Disney and Gathergood (2011), and Brown et al. (2013), among others.

Figure 1.1: Home equity extraction and house prices in the U.S.



Note: This figure displays the flows of home equity extraction (solid blue line, left scale) in the U.S. in billion of dollars along with the Shiller' Real Home Price Index (dashed green line, right scale). Home equity extraction is computed as a four quarters moving average of Gross Equity Extraction divided by the Consumer Price Index. The series, computed according to the methodology in Greenspan and Kennedy (2005), is available at http://www.calculatedriskblog.com/2009/03/q4-mortgage-equity-extraction-strongly.html (retrieved 7 August 2014). The Real Home Price Index is available at the Robert Shiller's website (http://www.econ.yale.edu/~shiller/data.htm, retrieved 7 August 2014).

expected value of their houses. We show that long-run expectations about future house prices of both households and, especially, financial intermediaries have a large impact on households' indebtedness. Our story relates to the work of Fuster et al. (2010) and Fuster et al. (2012) and to the concept of *natural expectations*. Indeed, these papers build on an asset-pricing setting in which: (1) fundamentals of the economy are truly hump-shaped, exhibiting momentum in the short run and partial mean reversion in the long run, which, however, is hard to identify in small samples; and (2) agents do not know that fundamentals are hump-shaped and, instead, base their beliefs on parsimonious models that fit the available data. We adopt a similar approach to the housing-credit market, assuming that our economy's homeowners take housing prices as given; they derive long-run house price forecasts in order to quantify their future housing wealth and to decide how much equity to extract. Similarly, financial intermediaries need to forecast future house prices to choose the supply of home equity loans.

Which model do agents use to forecast housing prices? We consider a set of parsimonious models that replicate empirically observed patterns in housing prices. Hence, these models are similar in terms of in-sample fit and short-run forecasts. However, they differ in their ability to capture the long-run hump-shaped dynamics that characterize housing prices. We are interested in assessing how the behavior of agents in the credit market is affected by *natural* expectations - that is, the tendency to base forecasts on simplified models that fail to take into account the long-run mean reversion of house prices after a positive short-run momentum.[4] After all, as shown by Fuster et al. (2010), long-run mean reversion is a property that is hard to detect in small samples. Then, using a tractable model of a collateralized credit market populated by households and banks and calibrated to the recent house price boom-bust episode, we find that: (1) mild variations in long-run housing price forecasts result in quantitatively considerable differences in the amount of home equity extracted during a boom; (2) home equity extraction data are better matched by models in which agents are fairly *natural*; (3) the equilibrium level of debt and its interest rate are particularly sensitive to financial intermediaries' *naturalness*. Our findings, hence, support the theory of Case et al. (2012), which highlights the role of future housing price expectations in explaining cycles in the housing market.[5]

The assumption that households behave in line with the *natural* expectations theory when confronting house prices is largely supported by empirical work. For example, Goodman and Ittner (1992) surveys the early literature about the excessive optimism of homeowners in assessing the future values of their homes and documents that households overestimate home price by between 4 percent and 16 percent. Homeowners appear to overestimate even the current value of their houses: Agarwal (2007) considers panel data from 2002 to 2005 and concludes that homeowners overestimate their house value by on average 3.1 percent. Also, using survey data in the period 2002-2012, Case et al. (2012) find that households' forecasts were accurate in the short-

[4] As in Fuster et al. (2010), for tractability we abstract from learning and give agents a fixed, simple model estimated using available data. For a model of the Great Recession in which agents learn about the parameters of financial shocks see Pintus and Suda (2015).

[5] In this respect, our paper is also in line with Burnside et al. (2011), which show that boom and bust dynamics in the housing market are affected by "social dynamics" that lead agents to change beliefs about future housing prices. Other theories proposed in the literature focus on: growing complacency of lenders in the face of declining loan quality (Mian and Sufi, 2011, Demyanyk and Van Hemert, 2011); money illusion on the part of homebuyers that led to flawed comparisons of home purchase prices with rents (Brunnermeier and Julliard, 2008); an agency problem afflicting the credit rating agencies (Mathis et al., 2009); and government failure to regulate an emerging shadow banking system (Gorton, 2010).

run (one year) but "abnormally high" in the long run (10 years).[6] Similar evidence have been documented in Shiller (2007) and Benitez-Silva et al. (2008). Nevertheless, households are only one side of the housing-related debt market. In fact, financial institutions supply credit to households and, if they did not share the same optimistic forecasts, they would be reluctant to provide home equity loans at low interest rates. One novelty of this paper is its insight in documenting that financial experts also had *natural* expectations when they made their housing price forecasts - in the sense that they, too, ignored any form of long-run mean reversion in housing prices after the positive and strong short-run momentum. Thus, the first contribution of our paper is to document that financial experts also likely ignored hump-shaped dynamics of housing prices in their forecasts, and thus wound up being excessively optimistic about long-run housing price appreciation in the recent price boom. Specifically, we gather a unique dataset of out-of-sample housing price forecasts made by a professional forecasting company in the period 1995-2011 and show that these forecasts do not display any sort of adjustment after a period of short-run positive momentum: forecasts made prior to 2006 predict constant and large increases in long-run housing price until 2030. These findings are in line with other studies about the behavior of housing market experts during the boom phase.[7] We argue, then, that financial experts can also be treated as *natural* agents and that their inability to account for hump-shaped housing price dynamics affected the supply of credit during the recent boom.

As a second contribution of the paper, we apply the theory of *natural* expectations to the housing market. Specifically, first we show that housing prices are characterized by hump-shaped dynamics, which imply a large momentum in the short run and partial mean reversion in the long run. Then, we compare four models to estimate and forecast housing price dynamics. We consider two possible dimensions that lead to *natural* expectations: (1) an inner tendency of agents to incorporate a small set of explanatory variables when estimating a model, in line with the findings in Beshears et al. (2013); and (2) a limited ability of agents to consider a large set of data when estimating the model, in line with the assumption of extrapolative expectations applied to the housing market.[8] We also consider two rigorous and

[6] As the authors state: "it may be a general expectation about the vague and distant future that helps explain why people behaved in the 2000s as if they thought that home prices could never fall: perhaps they thought so only about the long run, as our 10-year expectations data seem to confirm".

[7] See Foote et al. (2012) and Cheng et al. (2014).

[8] See Goetzmann et al. (2012), Abraham and Hendershott (1994), Muellbauer and Murphy

more sophisticated statistical approaches to modeling and forecasting housing prices, which differ in the information criterion used to select the most appropriate specification. We find that models that incorporate hump-shaped dynamics are not preferred, in terms of in-sample fit, to more parsimonious models that ignore long-run mean reversion. As a result, the use of simple models leading to natural beliefs is fully justifiable in terms of in-sample performance. Finally, we demonstrate that models that have diverse degrees of ability to capture hump-shaped dynamics in housing price market may differ in their long-run forecasts, while leading to similar short-run predictions. Hence, agents that make use of simple models fail to take into account the partial mean reversion of housing prices in the long run.[9]

The third contribution of the paper is to link long-run housing price forecasts to the optimal behavior of agents in the credit market. We therefore introduce a tractable model of a collateralized credit market populated by a representative household and bank. The household can obtain credit from the bank by pledging its house as collateral.[10] In each period, the household decides how much to consume and how much to borrow and, given the realization of the stochastic exogenous housing price, whether to repay its debt or to default and lose the ownership of the house. The amount of debt demanded crucially depends on the expected realizations of the housing price. The bank borrows resources at a prime rate and lends them to the household charging a margin. The bank gains either from debt repayment, in the case of no default from the household, or from the sale of the housing stock, in the case of default. Obviously, the banks' expected future house price is a key determinant of its supply of credit.

In our quantitative assessment, we are mainly interested in examining the extent to which the equilibrium level of debt and its price vary with the ability of agents to take into account possible long run mean-reverting dynamics of housing prices. Hence, we select a housing price path in our model that matches the observed dynamics of the aggregate U.S. housing price in the period 2001-2010, and we vary the specification of the process the agents use to predict future house prices. We consider a large set of specifications (fifty) that are identical in terms of the short-run (one-year ahead) forecast, and in terms of magnitude of the unconditional variance of the housing price

(1997) and Piazzesi and Schneider (2009).

[9] As discussed in Fuster et al. (2010): "there are several reasons that justify the use of simple models: they are easy to understand, easy to explain, and easy to employ; simplicity also reduces the risks of over-fitting".

[10] The model is related to Cocco (2005), Yao (2005), Li and Yao (2007), Campbell and Cocco (2011), and Brueckner et al. (2012).

process, but that differ in terms of the long-run expectations. Hence, we can rank the different specifications according to their degree of *naturalness*: more *natural* processes ignore the long-run mean reversion of housing prices and predict a higher long-run price; less *natural* processes incorporate a certain degree of housing price adjustment after the short-run momentum and predict a lower long-run price. We find four results. First, the model predicts a positive relationship between the average equilibrium level of debt in the economy in the boom phase and the degree of *naturalness* of agents. Intuitively, after observing an increase in the house price, a more *natural* agent expects a longer-lasting housing price appreciation, which gives stronger incentive to demand/supply debt. Second, long-run expectations play a large role from a quantitative point of view: when the economy is populated by more *natural* agents, the debt to income ratio during a boom phase is about 55 percent; when the economy is populated by less *natural* agents it falls to 35 percent. Recall that the difference in these quantities is solely due to the contrasting long-run expectations of housing prices, since by construction agents have the same short-run expectations in each of the fifty specifications. Third, we show that the supply-side *naturalness* is particularly important for the increasing household debt leverage during the housing price boom and for the interest rate reduction of home equity loans, as documented by Justiniano et al. (2014). In fact, by conducting a simple experiment where only the bank or the household (or both) are natural, we highlight that banks' *naturalness* has a larger effect than households' *naturalness* in increasing the equilibrium level of debt in the economy. The intuition for this result stems from the fact that default in our model is a cost for households but a revenue for the bank and this cost/revenue is increasing in the expected housing price. As a last result, using data on Gross Home Equity Extraction as computed in Greenspan and Kennedy (2005), we show that the simulated process that better fits the observed debt dynamics during the 2000-2009 episode is characterized by a rather high degree of *naturalness*.

The rest of the paper is organized as follows. In section 1.2 we provide evidence that financial experts' forecasted future housing prices were not able to incorporate their long-run downward adjustment after a positive momentum. In section 1.3 we discuss the properties of *natural* expectations and their implications for long-run housing price forecasts. In section 1.4 we describe the theoretical model, and in section 1.5 we describe its calibration. In section 1.6 we discuss the quantitative results of the model. Section 1.7 concludes and summarizes the main findings.

1.2 Financial Experts Forecasts

The goal of this paper is to analyze the interaction between housing price forecasts and private agents' economic behavior in the credit market. In this section we provide evidence that models used by financial experts to forecast future housing prices were not able to incorporate their long-run downward adjustment after a positive momentum, which led to too optimistic future housing price expectations. For this reason, it is not unreasonable to consider financial experts as *natural agents*, in the sense that, as Fuster et al. (2012) define, they have ignored the hump-shaped dynamics of the housing price process that indeed characterize the housing price data, as we document later in the paper.

Specifically, we analyze a unique data set that contains out-of-sample forecasts of quarterly housing prices up to a horizon of 30 years, produced by a professional forecasting company.[11] The model used for generating the forecasts is described as a rich demand-supply model that takes into account long-term influences on housing prices, such as income trends and demographics, and cyclical factors such as unemployment and changes in mortgage rates. These forecasts begin in 1995 and were updated every quarter until the end of 2011. We take these forecasts as a proxy for the forecasts made by financial experts. We believe that since these forecasts were made by a professional forecasting company they are not subject to a "bad incentive" bias. Specifically, Barberis (2013) suggests that financial institutions might have had incentives to sell real estate financial instruments even when predicting a coming house price collapse. The fact that our dataset is not provided by a lending institution rules out the possible problem that these forecasts were simply strategic statements to sell specific product to clients. Our underlying assumption is, then, than these forecasts collect what financial experts really expected about the future evolution of house prices.

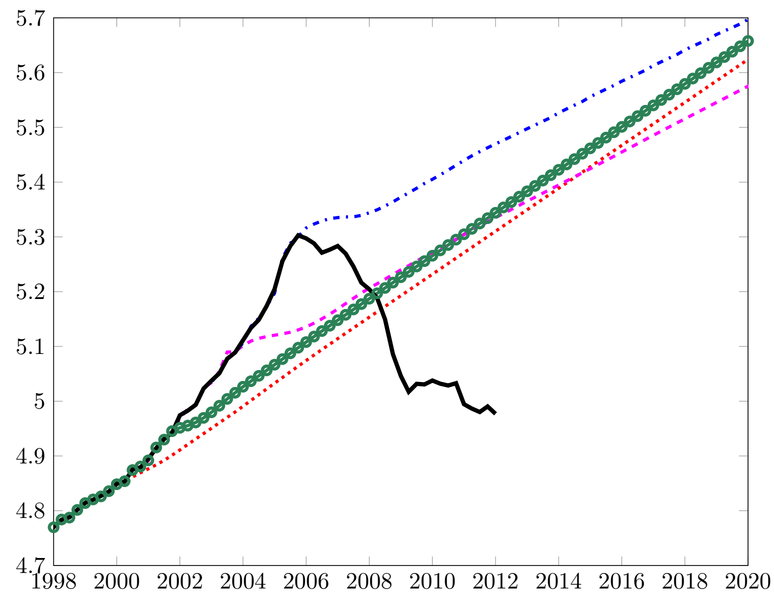
Figure 1.2 shows the professional forecasts of a nominal housing price index for the period 1998-2020.[12] In this figure we consider four forecasts made in the period 1998-2006, before the bust of the housing bubble. The

[11] This globally recognized professional forecasting company provided us with their nominal housing price out-of-sample forecasts generated by their models. Unfortunately, the company was willing to privately disclose to us point estimates only.

[12] For greater transparency, we plot the nominal house price index because it is the one directly provided to us by the forecasting company. We have also computed forecasts for real housing price, by assuming different projections of inflation, such as a constant 2 percent rate, a constant 1 percent rate, a rate forecasted by linear models. All these scenarios about inflation lead to very similar figures as the one reported for nominal prices. Hence, we decided to just show the latter.

red dotted line represents the forecast made in 2000Q1, the green circled line represents the forecast made in 2002Q1, the purple dashed line represent the forecast made in 2004Q1, and the blue dash-dotted line is the forecast made in 2006Q1.

Figure 1.2: Financial Expert's Forecasts



Note: This figure displays the realized evolution of the house price index (solid black line) along with the financial expert forecasts made in different points in time. The four forecasts in the figure were made in 2000Q1 (red dotted line), in 2002Q1 (green circled line), in 2004Q1 (purple dashed line) and in 2006Q1 (blue dash-dotted line)

As the figure displays, the forecast made in 2000, 2002, and 2004 were relatively accurate in the short run. Nevertheless, the forecasts computed in those three years were not able to capture the steep price appreciation that characterized the period 2000-2007. Furthermore, and most importantly, all the forecasts were completely unable to predict the large housing price bust experience in 2006. Notice that the forecasters expected overall constant and large increases in long-run housing prices for the period 2000-2030.

We argue that these forecasts are consistent with the assumption that professional forecasters also failed to take into account any sort of long-run mean reversion in housing prices.

To support this point, in Table 1.1 we compute the x-quarters ahead forecasts for each year in which the forecast was made. We consider both short-run forecasts (x=1,4,8) and long-run forecasts (x=20,40,80). We normalize the housing price in the quarter in which the forecast was made to 100, and we analyze the dynamics of the forecast in relation to that value. Three main properties of the forecasts emerge from Table 1.1. First, forecasts made throughout the period 1995-2006 predicted large housing price appreciation. Second, the dynamics of the forecasts as a function of the horizon are roughly independent of the period in which the forecast was made. In fact, all of the forecasts imply increasingly large appreciations of housing prices over time: the one-year-ahead forecasts imply increases of 2 percent to almost 4 percent; the five-year-ahead forecasts imply increases of 15 percent to 22 percent; the 10-year-ahead forecasts imply increases of 34 percent to 47 percent; and the 20-year ahead forecasts imply increases of 79 percent to 113 percent. Although the magnitude of the forecasted appreciation varies, we argue that throughout the period 1995-2006 there is no evidence of an adjustment in terms of housing price forecasts.

Table 1.1: Nominal Growth Forecasted House Price

	Forecasts $t+q$					
$q=$	1	4	8	20	40	80
$t=$						
1995	103.2	103.8	106.9	119.9	145.8	215.9
1998	100.9	102.8	106.7	119.5	146.5	223.1
2000	100.9	103.3	106.9	120.7	147.4	218.1
2002	100.4	102.8	107.8	121.7	136.9	219.2
2004	100.8	101.9	103.5	114.8	134.0	181.8
2006	100.8	103.5	106.6	116.2	133.9	179.5

Note: This table reports q-quarters ahead normalized forecasts by the professional forecast company made in the first quarter of the year reported in the first column.

The reported forecasts suggest that it is not unreasonable to assume that financial experts might also have been exposed to some source of bias that led them to ignore the mean-reversion component of housing prices growth. These findings are in line with other studies on the behavior of housing market experts during the boom phase. Gerardi et al. (2008) show that analysts and experts attached a very low probability to a significant reduction in house prices, while Cheng et al. (2014) find that securitization agents were on average not aware of the overvaluation of the housing market.[13] The optimism about house prices is reflected in the risk (and the subsequent losses)

[13]Interestingly, their study finds that "certain groups of agents - those living in bubblier areas, working on the sell side, or at firms with greater exposure to subprime mortgages -

borne by financial intermediaries, which kept the vast majority of second liens on their balance sheets, while securitizing first-lien mortgages.[14]

The main conclusion we draw from this section is that professional forecasters were most likely making use of models that were not able to capture any sort of mean reversion in long-run housing price dynamics. In this regard, we can state that financial experts displayed *natural expectations*, as we will formally define in the next section. Even though financial experts- unlike households - commonly make use of large and convoluted models to generate forecasts, it seems evident that the internal propagation mechanisms of these models are inadequate to the task of capturing the long-run mean reversion pattern that characterizes housing prices. In this sense, our evidence supports the hypothesis proposed by Barberis (2013) that financial experts used "bad models" for predicting future housing prices and that these models let them to be too optimistic about future values of collateral. This has likely affected the supply of credit, as we show in the next sections.

1.3 Natural House Price Expectations

The main goal of this paper is to link the inability of agents to forecast long-run hump-shaped dynamics of housing prices and the amount of housing-related debt demanded or supplied. In this section we show three results that establish this linkage. First, it is, indeed, likely that housing prices are characterized by hump-shaped dynamics, which imply momentum in the short run and partial mean reversion in the long run. Second, we document that models that incorporate hump-shaped dynamics are not preferred, in terms of in-sample fit, to more parsimonious models that ignore long-run mean reversion. As a result, the use of simple models leading to natural beliefs is perfectly justifiable in terms of in-sample performance. Third, we demonstrate that, nevertheless, forecasts based on models with diverse degrees of ability in capturing the hump-shaped dynamics of housing prices differ over long-run horizons but not in the short-run. Hence, if agents use simple models (for a wide range of good reasons[15]), they fail to forecast the partial mean

may have been particularly subject to potential sources of belief distortions, such as job environments that foster group think, cognitive dissonance, or other sources of over-optimism."

[14]See for instance Figure 4 from "Residential Credit Losses - Going into Extra Innings?" Lehman Brothers U.S. Securitized Products, April 11, 2008 (reprinted in Acharya et al. (2009)), where it is shown that a relevant fraction of HELOCs and second-liens were kept in the balance sheets of US banks.

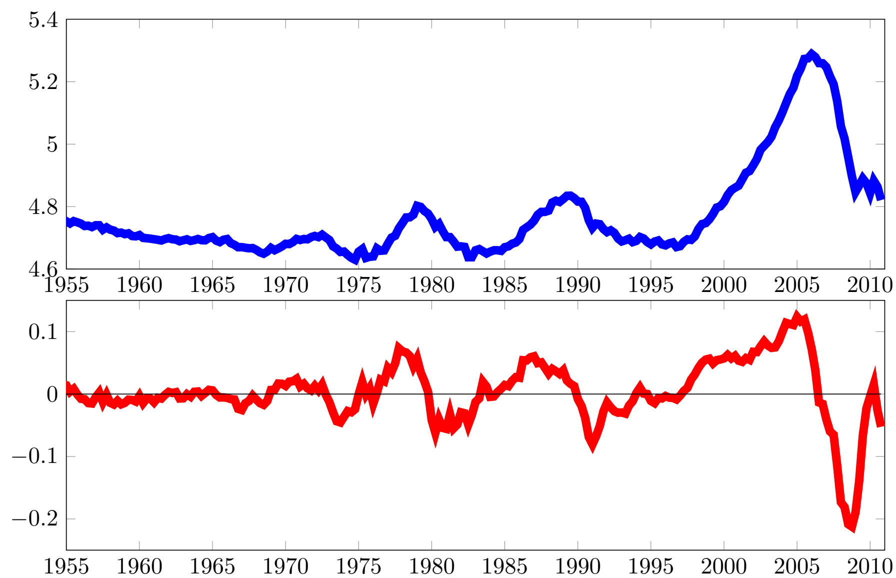
[15]As Fuster et al. (2010) put: "simple models are easier to understand, easier to explain, and easier to employ; simplicity also reduces the risks of overfitting. Whatever the mix of

reversion in housing prices over the long run (this is in line with the pattern shown by the financial experts' forecasts documented in the previous section). Following Fuster et al. (2010), we call the resulting beliefs of these agents *natural expectations*.

Modeling Natural Expectations for Housing Prices

In this section we examine data on the aggregate real U.S. housing price index to see how different modeling approaches vary in their ability to capture hump-shaped long-run dynamics. The series of interest is the quarterly Standard & Poor's Case-Shiller Home Price Index for U.S. real housing prices in the sample 1951:1-2010:4. The logarithm of the raw series is plotted in the upper panel of Figure 1.3. The series displays at least four episodes of boom and bust: the first one in the early '70s, the second one later in the decade, the third one in the '80s, and, finally, the most recent and significant from 1997 to 2005.

Figure 1.3: Real U.S. Shiller House Price index



Note: This figure plots the Standard & Poor's Case-Shiller Home Price Index U.S. real housing price index in its level (upper panel) and growth rate (lower panel).

reasons -pragmatic, behavioral, and statistical- economic agents usually do use simple models to understand economic dynamics".

The series is statistically characterized by the presence of a unit root.[16] We therefore consider as a variable of interest its yearly growth rate, displayed in the bottom panel of Figure 1.3. Notice also that the growth rate of housing prices is characterized by relatively long periods positive growth followed by abrupt declines, which indicate the presence of a rich autocorrelation structure.

We then assume that the process for housing price growth rate, g_t, is autoregressive,[17] i.e.:

$$\left(1-\Phi_p\left(L\right)\right)g_t=\mu+\varepsilon_t, \tag{1.1}$$

where $\Phi_p\left(L\right)$ is a lag polynomial of order p, μ is a constant, and ε_t are iid innovations.

We assume that an agent could estimate the model in equation (1.1) using four different criteria that gather a spectrum of different approaches to estimation and forecasting. Initially, we propose two simple models that capture *natural expectations* on housing prices. Recall that, as in Fuster et al. (2010), we define *natural expectations* as the beliefs of agents that fail to incorporate hump-shaped long-run dynamics of the fundamentals. We explore two possible dimensions that lead to *natural expectations*: (1) a limited ability of agents to incorporate a large set of explanatory variables when estimating a model; and (2) a limited ability of agents to consider a large set of data when estimating the model. Regarding the first model, we assume that an agent naively considers a first order polynomial, that is $p=1$ and $\Phi_p\left(L\right)=1-\phi_1L$ when estimating equation (1.1). This assumption captures behavioral biases, such as a natural attitude to use over-simplified models, as in Beshears et al. (2013) and in Hommes and Zhu (2014). We refer to this model as *intuitive expectations*, consistently with Fuster et al. (2010). Regarding the second model, we

[16] To formally test the null hypothesis of presence of a unit root in the house price level, we run the Phillips and Perron (1988) unit root test. We allowed the regression to incorporate from 1 to 15 lags. For any of these specifications the test could not reject the null hypothesis of the presence of a unit root. To check whether the presence of a unit root is driven by the 1997-2007 price boom, we run the test for the shorter sample 1953:1-1996:4. Also in this case, the Phillips-Perron test could not reject the null hypothesis at a 5 percent significance level for any model specifications. In addition, there is no statistical evidence that the house price of growth rate contains unit roots.

[17] Our modeling choice is justified by Crawford and Fratantoni (2003) who show that linear (ARMA) models are preferred to non-linear housing price models for out-of-sample forecasts. As a robustness check, we have alternatively assumed that the housing price growth rate g_t is an ARMA process of the form $\left(1-\Phi_p\left(L\right)\right)g_t=\mu+\left(1+\Theta_q\left(L\right)\right)\varepsilon_t$, where $\Theta_q\left(L\right)$ is a lag polynomial of order q. The BIC chooses an ARMA(1,4), whereas the AIC chooses an ARMA(18,5). The impulse response functions are very similar to the one reported in this section when assuming an AR process.

assume that an agent has finite memory and accordingly forecasts the model in equation (1.1) by considering only the most recent observations. In particular, we assume that agents consider only the last $T^{lim} = 100$ observations when estimating the model.[18] The underlying assumption is that agents using this model do not take into account earlier historical housing price dynamics, either because they do not have access to those data, or because they ignore them, or simply because they assign much lower weight to older observations. We refer to this model as *finite memory*.[19] Notice that the *finite memory* model captures a source of bias that does not emerge because of a possible model misspecification (as for the *intuitive expectations* model), but the bias depends upon the limited amount of information that is relevant for the agent when estimating the model.[20]

We then compare the implications of these *natural expectations* models with the ones produced by more rigorous and sophisticated statistical approaches. In fact, an agent could, to the contrary, make use of more sophisticated econometric techniques to estimate the more appropriate lag polynomial in equation (1.1). When choosing how many parameters to include, a modeler faces a trade-off between improving the in-sample fit of the model and the risk of overfitting the available data, which may result in poor out-of-sample forecasts. Two of the most popular criteria are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). It is not clear which criterion should be preferred by practitioners in small samples.[21] an therefore we retain both, considering as third and fourth models the specification of equation (1.1) obtained when an econometrician uses respectively the AIC criterion and the BIC criterion.

In Table 1.2 (left panel for the whole sample 1953:1-2010:4) we report point estimates (standard errors in brackets) for four models: $p = 1$, estimated

[18] We obtain similar results when varying T^{lim} in the range 80-120.

[19] There are other interpretations for this approach. For example, agents might have adopted a "new-era thinking", which referes to agents deliberately excluding less recent observations because they believe they are not relevant anymore. Alternatively this approach can also capture the assumption of extrapolative expectations in the housing market employed by Goetzmann et al. (2012), Abraham and Hendershott (1994), Muellbauer and Murphy (1997), Piazzesi and Schneider (2009), and it relates to the findings of Agarwal (2007) and Duca and Kumar (2014), which state that younger individuals have statistically significant more propensity to overestimate house prices and to withdraw housing equity, respectively.

[20] We assume that the agent with finite memory estimates the model by maximizing information criteria. Since the BIC and AIC select the same length for the lag-polynomial, the two approaches deliver the same results.

[21] See McQuarrie and Tsai (1998) and Neath and Cavanaugh (1997) for opposing arguments.

with an *intuitive* model; $p = 6$, estimated with a *finite memory* model; $p = 5$, estimated with the BIC model; $p = 16$, estimated with the AIC model.

Table 1.2: Estimation of House Price Growth

	Whole Sample: 1953:1-2010:4				Subsample: 1953:1-1996:4			
	Intuitive	Finite memory	BIC	AIC	Intuitive	Finite memory	BIC	AIC
ϕ_1	0.958^{***} [0.02]	1.636^{***} [0.10]	1.330^{***} [0.06]	1.348^{***} [0.07]	0.914^{***} [0.00]	1.129^{***} [0.10]	1.052^{***} [0.08]	1.118^{***} [0.08]
ϕ_2		-0.581^{***} [0.19]	-0.221^{**} [0.10]	-0.241^{***} [0.11]		-0.153 [0.14]	-0.024 [0.11]	-0.136 [0.13]
ϕ_3		0.100 [0.19]	0.090 [0.10]	0.122 [0.12]		0.219 [0.14]	0.113 [0.11]	0.194 [0.12]
ϕ_4		-0.789^{***} [0.18]	-0.614^{***} [0.10]	-0.841^{***} [0.12]		-0.540^{***} [0.14]	-0.695^{***} [0.11]	-0.805^{***} [0.12]
ϕ_5		0.850^{***} [0.19]	0.355^{***} [0.06]	0.656^{***} [0.12]		-0.245^{***} [0.10]	-0.540^{***} [0.12]	0.652^{***} [0.14]
ϕ_6		-0.259^{**} [0.11]		0.012 [0.13]			0.077 [0.13]	0.004 [0.14]
ϕ_7				-0.060 [0.13]			-0.073 [0.13]	-0.006 [0.14]
ϕ_8				-0.457^{***} [0.13]			-0.459^{***} [0.13]	-0.562^{***} [0.14]
ϕ_9				0.346^{***} [0.13]			0.425^{***} [0.12]	0.485^{***} [0.14]
ϕ_{10}				0.055 [0.13]			0.049 [0.11]	0.013 [0.14]
ϕ_{11}				0.121 [0.14]			0.039 [0.11]	0.148 [0.14]
ϕ_{12}				-0.631^{***} [0.13]			-0.467^{***} [0.11]	-0.653^{***} [014]
ϕ_{13}				0.285^{**} [0.12]			0.218^{***} [0.08]	0.403^{**} [0.14]
ϕ_{14}				0.050 [0.13]				-0.118 [0.12]
ϕ_{15}				0.136 [0.13]				0.211^{*} [0.12]
ϕ_{16}				-0.119 [0.08]				-0.291^{**} [0.08]
ϕ_{17}								0.105 [0.08]

Note: In this table we report the estimates of the autoregressive process in equation (1.1) when considering four models. The *intuitive* expectations model assumes a first order autoregressive process. The *finite memory* assumes that the agents estimate the model by using only the most recent 100 observations and select the order of the lag polynomial by considering the Bayesian Information Criterion. The BIC and AIC models are estimated by maximizing the two different information criteria when using observation from the whole sample (1953:1-2010:4) (left panel) and in the subsample (1953:1-1996:4) (right panel). The real housing price is the annual growth rate of the Shiller index. Standard errors are in brackets. Significance at 1 percent is indicated by ***, at 5 percent by **, at 10 percent by *.

Notice that there is a remarkable difference in the number of lags selected by the last two models: since the BIC criterion largely penalizes overfitting, it select much fewer lags than the AIC criterion. Furthermore, the large number of significant parameters for lags greater than one, in particular for the AIC model, confirms that the process of housing price growth has a relatively rich autoregressive structure. Consequently, an agent who makes use of a simpler autoregressive model is likely to ignore important dynamics of house price growth. The different long-run implications of the models are summarized by their resulting long-run persistence, as discussed in detail below. Notice that these findings are robust to considering only a more limited sample (1953:1-1996:4) that does not include a recent housing price boom, as reported on the right panel of Table 1.2.

In-sample Fit and Long-Run Predictions

In the previous section we have reported the estimates of four different specifications of a linear model for housing price growth. In this section we provide evidence that, although drastically contrasting in their underlying assumptions, these specifications have similar in-sample properties, and they are hardly distinguishable from a statistical point of view. Table 1.3 reports statistics about the goodness of fit of the four models.

Table 1.3: In-Sample Fit and Forecasts

	Intuitive ($p = 1$)	finite memory ($p = 6$)	BIC ($p = 5$)	AIC ($p = 16$)
RMSE	0.0148	0.0122	0.0122	0.0113
R^2	0.9130	0.9713	0.9417	0.9531
$\bar{R}^2$ (adj.)	0.9126	0.9694	0.9404	0.9496
log-likelihood	636.58	682.90	681.14	700.72
p-value LR test (against AR1)			0.13	0.19
One period Ahead Forecast	1.96	2.63	2.33	2.34
Confidence Bands (95%)	[1.90; 1.97]	[2.31;2.82]	[2.18; 2.44]	[2.18; 2.48]
Long-Run Persistence (LRP)	23.7	24.4	18.7	10.4
Confidence Bands (95%)	[10.3; 31.4]	[6.4; 59.5]	[8.6; 28.9]	[5.1; 17.7]

Note: The top panel of this table reports the in-sample fit statistics for the four models for model for housing prices (Intuitive expectations, finite memory model, and for the model selected by the BIC and by AIC). The bottom panel reports statistics regarding the properties of the models about the short-run forecasts and long-run forecasts.

The Root Mean Squared Error (RMSE), the unadjusted coefficient of determination (R^2), and the adjusted coefficient of determination ($\bar{R}^2$) are very similar across the models.[22] Since the *intuitive* model, the BIC model, and the AIC model are all nested models, we can formally test whether the data can formally reject the null hypothesis that the three models are observationally similar by comparing the log-likelihood evaluated at the unrestricted model parameter estimates and the restricted model parameter estimates. As Table 1.3 displays, the resulting Likelihood Ratio (LR) test statistics when assuming that the restricted model corresponds to $p = 1$ and the unrestricted model corresponds to $p = 5$ and $p = 16$, respectively, confirm that the models cannot be distinguished on the basis of goodness-of-fit alone. Since the *finite memory* model considers a different sample, it cannot be nested in the other three models. Hence, the LR test cannot be performed. Nevertheless, notice that its likelihood is very similar to the one of the other three models. Notice, too, that the one-quarter-ahead forecasts produced by these models are also similar.

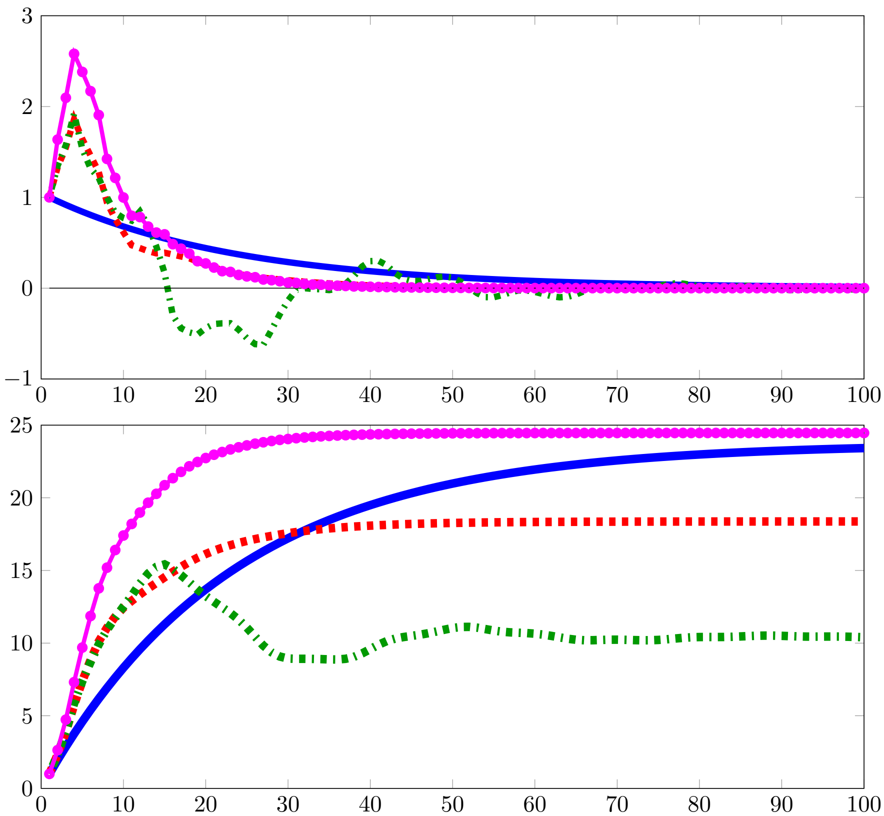
Although the models imply a similar fit to the data and similar short-run predictions, their long-run out-of sample forecast implications are different. We can observe these features of the models by plotting the impulse response functions for a 1 percent positive shock in the housing price growth rate, as displayed in the top panel of Figure 1.4.

The *intuitive* model (solid blue line) estimates a very persistent process, as indicated by the value of the parameter of the AR(1) process, equal to 0.96 as reported in Table 1.2. Consequently, it predicts a long-lasting positive effect of a shock on housing price growth. In contrast, the BIC model (dashed red line) and the AIC model (dotted green line) predict larger short-run responses of housing prices, but they estimate faster reversions after 10-15 quarters. Notice, also, that the practitioner who uses the AIC criterion estimates a negative medium-run response of price-growth after the large boom, but even this model does not particularly succeed of incorporating a large mean reversion component of house price. This fact shows that it is hard to obtain mean-reversion dynamics even with more sophisticated models when estimated in small samples. Finally, the *finite memory* model (dotted purple line) has a very large short-run response and implies a persistence of the positive shock for about 30 quarters, without any sort of mean reversion.

We can obtain insights about the different long-run predictions of the models by plotting the impulse responses of the level of the housing prices,

[22] Although we do not report them here, the historical in-sample fitted values of the four models are basically indistinguishable. Therefore, they the different empirical models have a very similar ability to capture the in-sample boom-and-bust episodes.

Figure 1.4: Comparison of Impulse Response Functions



Note: This figure reports the impulse response function (IRF) of housing price growth rate (upper panel) and housing price level (lower panel) to a positive unitary shock. The solid blue line represents the IRF implied by agents that estimate an AR(1) process for the housing price growth rate (intuitive model). The solid-dotted purple line represents the IRF implied by an agents that estimate a process for the housing price growth rate when using only the last 100 observations (finite memory model). The dotted red line represents the IRF for an agent that maximizes the Bayesian Information Criterion and, hence, estimates an AR(5) process for the housing price growth rate. The green dashed line represent the IRF for an agent that maximizes the Akaike Information Criterion and, hence, estimates an AR(16) process for the housing price growth rate.

as displayed in the lower panel of Figure 1.4. These responses are given by the cumulative sum of the impulse responses of the growth rate. An agent using the *finite memory* model (dotted purple line) predicts that, after a positive shock, housing prices will largely increase for about 25-30 quarters and then stabilize at a high level. An agent using the *intuitive* model (solid blue line) expects a longer persistence of housing price appreciation, which leads to a similar long-run forecasts as with the *finite memory* model. The two more sophisticated models (BIC model, dashed red line, and AIC model, dotted green line) predict a much lower degree of persistence, which leads to lower expected long-run prices. In fact, they prove better in capturing the mean-reversion feature of housing prices than both the *intuitive* model and the *finite memory* model. Notice also, that an econometrician using the AIC criterion expects a depreciation following the initial boom. Furthermore, since the four models are hardly distinguishable in the sample, as pointed out above, it is legitimate to conjecture that these impulse responses are associated with a large degree of uncertainty. Not surprisingly, this is indeed the case, as described in Appendix 1.8.

The long-run dynamics of housing prices are particularly important for the purpose of this paper. In fact, we conjecture that households' consumption-saving decisions are affected by the perceived long-run housing wealth. This presumption is motivated by the long durability of housing as an asset, and by the nature of home equity loans, which have repayment periods of up to 25 years. It is therefore reasonable to assume that long-run forecasts of housing prices matter for households' present decisions. A measure of the long-run price estimated after a shock is the long-run persistence of the price level, defined as the long run steady state level after a 1 percent shock. Given that the price level is assumed to follow an ARIMA(p,1,0) model, the long-run persistence (LRP) can be computed as:

$$LRP = \frac{1}{1 - \sum_{j=1}^{p} \phi_j}$$

where ϕ_j , $j = 1, ..., p$ are the coefficients of the lag polynomial of order p, $\Phi_p(L)$. Table 1.3 reports the LRP of the processes estimated by the four models as well as their confidence band.

As Table 1.3 reports, the LRP estimated with an *intuitive* model is larger than the one estimated by agents using a more rigorous statistical approach. In particular, the AR(1) model delivers a long-run persistence that is 30 percent higher than the AR(5) model selected by the BIC, and 80 percent higher than the AR(16) model selected by the AIC.[23] Also, the LRP estimated by the *finite memory* model is similar to the one estimated by the *intuitive* model. This an important result since it shows that agents who use oversimplified models (because of behavioral biases or sample selection) tend to have more optimistic expectations about long-run housing price resulting after a positive shock than agents using more sophisticated models. In Table 1.7 in Appendix 1.9 we report similar results obtained when considering annual data, confirming that our findings are not an artifact of data frequencies.

1.4 A Model for Home Equity Loans and Natural Expectations

In this section we propose a model in which a representative household and a representative bank interact in a market for home equity loans. Importantly, we allow agents to have a range of expectations upon the evolution of the exogenous housing price that varies with the ability of agents to incorporate long run mean reversion of house prices. Hence, the expectations vary from more *natural* (lower ability to incorporate long-run mean reversion) to less *natural* (greater ability to incorporate long-run mean reversion). Our theoretical model can be used as a laboratory to investigate the extent to which *naturalness* of households and banks has affected the level of debt in the economy during the housing price boom.

Household

The economy lasts $T < \infty$ periods and is populated by two representative agents: a household and a bank. There are a non-storable consumption good and two assets: housing and debt claims. The household starts at $t = 0$ with an endowment of housing stock h worth $p_0 h$, where p_t denotes the real housing price at time t, and the household is allowed to sell the house only in the final period, at a price p_T, unless it decides to default in any time $t = 1, ..., T-1$. In case of default, the household loses the ownership of the house and becomes a renter. Since the household starts with an owned housing stock and with no previous debt, and it does not engage in buying or selling

[23] As already stated, aa robustness check, we have alternatively assumed that the housing price growth rate g_t is an ARMA process. The BIC and the AIC pick respectively an ARMA(1,4), and an ARMA(18,5). Since the LRP (18.6 for ARMA(1,4) and 12.9 for the ARMA (18,5)) and the Impulse Response functions are very similar to the one estimated with the AR processes we decided to present only the latter.

its housing stock, we can interpret the debt claims in the economy as home equity extraction. We assume that the household is endowed in each period with a constant income $y_t = y > 0$. The housing price is an exogenous variable for the agents in our economy.[24]

Subject to the repayment of debt accumulated in the past, in period t the household is allowed to borrow new debt d_t which it will eventually repay in the next period at an interest rate of r_t. The household has the option of defaulting from $t = 1$ onwards. Hence, the budget constraint of a household that repays its debt at time t is:

$$c_t + (1 + r_{t-1})d_{t-1} = y + d_t;$$

whereas, the budget constraint of a household that decides to default at time t is:

$$c_t + \gamma p_t h = y,$$

where $\gamma p_t h$ represents the renting cost, which is assumed, for simplicity, to be a fraction γ of the house's value.

The household, then, maximizes its intertemporal utility:

$$E_0 \sum_{t=0}^{T} \beta^t u(c_t, h),$$

subject to the period-by-period budget constraint, which is conditional on the default decision. Later, we will discuss in depth how agents' expectations are formed. In each period the household's choice defines a debt demand schedule $d_t(r_t)$ and a related default decision.

We can rewrite the problem recursively and solve it by backward induction. Let us then start from period $t = T$: if the household has never defaulted in the past, in the last period it is entitled to sell its housing stock; hence the only decision variable is whether to default or not to default. Since the household sells the housing stock in the last period, there is no possibility of getting new debt, and, thus, consumption is simply determined by the exogenous income and housing value.

In case of a good credit history (i.e. no past default), the problem in period T can be then written as:

$$V_T^*(r_{T-1}, d_{T-1}, p_T) = \max\{u(y - \gamma p_T h); u(y - (1 + r_{T-1})d_{T-1} + p_T h)\}.$$

[24]This simplifying assumption is justified by this paper's goal of understanding how different expectations about the evolution of housing prices affect agents' economic behavior and is used in several studies on the effects of housing on macroeconomic or financial decisions, as in Campbell and Cocco (2011) or Cocco (2005).

Provided that the household did not default in the past, it has the option of defaulting in periods $t = 1, ..., T-1$. Hence, for $t = 1, ..., T-1$ the household has to compare two value functions: if it decides to default (or did so in the past), the value function writes:

$$V_t^D(p_t) = u(y - \gamma p_t h) + \beta E_t V_{t+1}^D(p_{t+1}),$$

with $d_\tau = 0$ for $\tau \geq t$. In the event that the household did not default in the past and is not defaulting in the current period t, the value function writes instead:

$$V_t^C(r_{t-1}, d_{t-1}, p_t) = \max_{d_t} \left[u(y - (1 + r_{t-1})d_{t-1} + d_t) + \beta E_t \left\{V_{t+1}^*(r_t, d_t, p_{t+1})\right\}\right].$$

Hence, in each period $t = 1, ..., T-1$, the household compares the two value functions to pin down its default choice:

$$V_t^*(r_{t-1}, d_{t-1}, p_t) = \max\left\{V_t^D(p_t); V_t^C(r_{t-1}, d_{t-1}, p_t)\right\}.$$

Finally, in period $t = 0$ there is no default choice, since the household is assumed to start with no debt; hence in $t = 0$ its value function reads:

$$V_0^*(p_0) = \max_{d_0} \left[u(y + d_0) + \beta E_t \left\{V_1^*(r_0, d_0, p_1)\right\}\right],$$

with the initial stock of debt $d_{-1} = 0$ given.

Bank

The bank seeks to maximize its intertemporal stream of profits, taking into account the probability of the household's default. In each period the bank obtains loans from outside the model at a risk-free rate, i_t and supplies credit to the household, at a market interest rate r_t. In case of default, the bank obtains revenues from liquidating the household's housing stock. The bank's problem can also be expressed in recursive form. Let's start from the last period, $t = T$. The profits for the bank write:

$$\pi_T(r_{T-1}, d_{T-1}, p_T) =$$

$$= \begin{cases} (1 + r_{T-1})d_{T-1} - (1 + i_{T-1})d_{T-1} & \text{if the household does not default} \\ & \text{(and did not default in the past)} \\ \kappa p_T h - (1 + i_{T-1})d_{T-1} & \text{if the household defaults} \\ & \text{(but did not in the past)} \\ 0 & \text{if the household defaulted} \\ & \text{in the past.} \end{cases}$$

Here κ represents the fraction of the collateral that the bank can recover after the household's default.

For a given interest rate r_t, in periods $t = 1, ..., T-1$ the bank sets d_t in such a way as to maximize its profits:

$$\max_{d_t} \pi_t \left(r_{t-1}, d_{t-1}, p_t\right) =$$

$$= \begin{cases} (r_{t-1} - i_{t-1})d_{t-1} + \delta E_t \pi_{t+1} \left(r_t, d_t, p_{t+1}\right) & \text{if the household does not default} \\ & \text{(and did not default in the past)} \\ \kappa p_t h - (1 + i_{t-1})d_{t-1} & \text{if the household defaults} \\ & \text{(but did not in the past)} \\ 0 & \text{if the household defaulted} \\ & \text{in the past.} \end{cases}$$

By assumption, the bank cannot default on its obligations. Finally, the profit function in $t = 0$ writes:

$$\pi_0 \left(p_0\right) = \delta E_0 \pi_1 \left(r_0, d_0, p_1\right).$$

Recursive equilibrium

A recursive equilibrium in our economy can be defined, for $t = 0, ..., T-1$, as an interest rate function $r_t(p_t, d_{t-1}, r_{t-1})$, a debt function $d_t(p_t, d_{t-1}, r_{t-1})$ and value functions $V_t^D\left(p_t\right)$, $V_t^C\left(r_{t-1}, d_{t-1}, p_t\right)$ and $\pi_t\left(r_{t-1}, d_{t-1}, p_t\right)$ such that in each period $t = 0, ..., T-1$ and for each realization of the housing price p_t and realizations of r_{t-1} and d_{t-1}:

- given r_t, $d_t(p_t, d_{t-1}, r_{t-1})$ and value functions $V_t^D\left(p_t\right)$, $V_t^C\left(r_{t-1}, d_{t-1}, p_t\right)$ solve the household recursive maximization problem.

- given r_t and providing that no default has occurred up to period t, $d_t(p_t, d_{t-1}, r_{t-1})$ and the profit function $\pi_t\left(r_{t-1}, d_{t-1}, p_t\right)$ solve the bank maximization profit.

- markets for the consumption good and debt clear.

  In period $t = T$ the household maximizes its utility under the budget constraint, choosing whether or not to default.

Expectation Formation

In our model we treat housing prices as exogenous and assume that the growth rate of the housing price follows a stochastic process. Accordingly, given a price of housing in the initial period, p_0, the evolution of the house price is given by:

$$p_{t+1} = p_t \left(1 + r^h_{t+1}\right),$$

with:

$$\left(1 - \Theta^p(L)\right) r^h_{t+1} = \sigma \varepsilon_{t+1}, \tag{1.2}$$

Here, r^h_{t+1} denotes the growth rate of housing price, $\Theta^p(L)$ is a lag polynomial of order $p > 1$, and ε_{t+1} is a mean-zero stochastic variable. This specification links the expectation of future house price growth rate to the autoregressive structure of the process, i.e.:

$$E_t r^h_{t+1} = \Theta^p(L) r^h_t.$$

As it will be clear next section, we examine the predictions of the model when varying the form of perceived expectation on future house prices by varying the properties of the lag polynomial $\Theta^p(L)$.

1.5 Calibration

By using the model described in the previous section, we now assess the quantitative effects of *natural* expectations in the consumption/saving decision. We are mainly interested in examining the extent to which the equilibrium level of housing-related debt and its price vary with the ability of agents to take into account possible long-run mean-reverting dynamics of house prices.

We consider an economy that lasts T=10 periods (years). The length of the simulation is a computationally restricted parameter, since in a non-stationary model the number of state-variables quickly explodes when increasing the number of periods in the model.[25] However, a 10-period time span is appealing for two reasons. First, it is long enough to fully capture a boom-bust episode such as the one observed in the U.S. housing market in

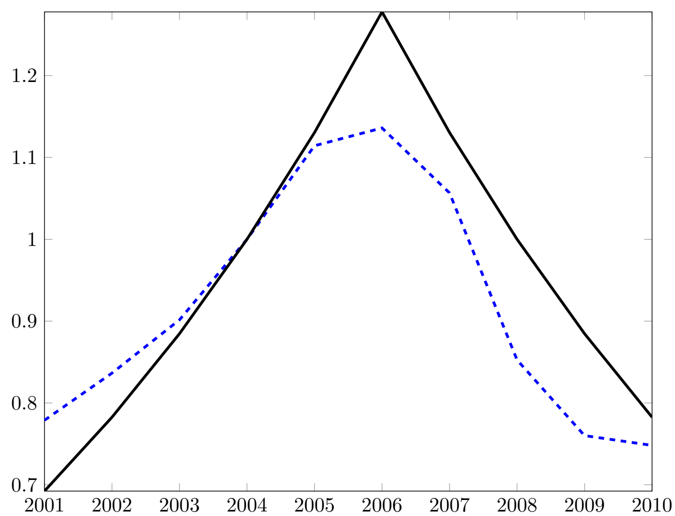
[25] Campbell and Cocco (2011), one of the closest models to ours, is simulated over a 20-years span. However, in order to keep the state space confined, they consider a *iid* housing price growth process, approximated by a bimodal Markov process. By reducing the length of the simulation to 10 periods, we are able to consider richer housing price dynamics, allowing for an autoregressive process approximated by a tri-modal Markov process.

the 2000s. Second, the majority of HELOCs started during the boom years had a duration of around 10 years.[26]

We conduct the following experiment. We feed the model with a given path of housing prices for 10 periods, which aims to replicate the boom-bust episode as experienced in the U.S. in the period 2001-2010. Then, we vary the agents' beliefs about the process generating the observed evolution of housing prices. Therefore, after observing the same initial housing price appreciation, different beliefs about the housing price data generating process affect the agents' optimal economic behavior.

The imposed evolution of housing price (solid line) is displayed in Figure 1.5.

Figure 1.5: Simulated house price dynamics



Note: This figure plots the housing price series fed into the model (black solid line) along with the actual realization of the annualized Shiller index from 2001 to 2010 (dotted line). The Shiller index has been rescaled and set equal to 1 in 2004.

Ultimately, we assume that agents in our model always observe the same evolution of housing prices and they rely on an autoregressive specification for the housing price growth rate in equation (1.2) of the form:

$$r^h_{t+1} = \Theta^p(L) r^h_t + \sigma \varepsilon_{t+1},$$

where $\Theta^p(L)$ is a lag polynomial of order $p > 1$. To investigate the impact of different forms of expectations, we consider a large set of specifications of

[26] From the Semiannual Risk Perspective From the National Risk Committee, U.S. Department of Treasury, 2012, it can be inferred that this portion was equal to at least 58 percent of loans outstanding in 2012.

$\Theta^p(L)$ that generate forecasts that are similar in the short run but different in the long run. It is important to note that we are completely silent about the true process that generated the observed housing price series as this is outside the scope of our analysis. In fact, in the empirical sections above, we showed that a large set of theoretical processes are consistent with the observed historical housing price time series. I

Calibrating Expectations

We consider 50 specifications for the model in equation (1.2) to generate agents' expectations of future housing prices. This large number of specifications allows us to investigate how macroeconomic variables respond to rather small differences in expectation formation. For computational feasibility, we limit our investigation to processes of order two, i.e.:

$$r_{t+1}^h = \mu(1 - \theta_1 - \theta_2) + \theta_1 r_t^h + \theta_2 r_{t-1}^h + \sigma\varepsilon_{t+1}. \tag{1.3}$$

Two important remarks about the choice of a second order autoregressive process are in order. First, considering a parsimonious process is paramount from computational reasons. Recall that our model is non-stationary and therefore we need to keep track of the value functions in each period. Adding more lags to the process will exponentially increase the number of state variables. Second, and more importantly, the AR(2) specification is flexible enough to capture features of the U.S. housing price index observed during the last boom-bust episode, and, above all, it allows us to incorporate different degrees of ability to embody hump-shaped dynamics.

As a result, each specification is a function of four parameters: μ, θ_1, θ_2, σ. We assume that the average growth rate of housing prices, μ, is known, and it is constant across each specification. In particular, we fix $\mu = 0$, which is consistent with the historical average growth rate of the real Shiller index between 1953 and 2000, which is equal to 0.00016. We make use of three criteria to pin down the remaining three parameters (θ_1, θ_2, σ) for each specification. First, each specification should produce the same short-run (one-year-ahead) forecasts. This assumption is motivated by the evidence in Case et al. (2012), which find that, in the short run, homebuyers were generally well informed, that their short-run expectations were not largely different from the actual realized home prices, and that most of the root causes of the housing bubble can be reconnected to their long-term home price expectations. Also this assumption is motived by the fact that *natural expectations* are able to capture short-run momentum, but fail to predict more subtle long-run mean reversion. Second, each specification should imply the same unconditional variance. As a consequence, the different behavior implied by each specification does not depend upon the magnitude of the housing-price variance, but only upon its propagation. Third, and most important, each specification should be characterized by different long-run forecasts. As a result, each specification differs only by the degree by which it is able to capture some sort of long-run mean reversion, when keeping fixed the short-run predictions and the overall variance of the process. Specifically, we set the first order autoregressive parameter, θ_1, to be equal to 0.6, which is the persistence of an AR(1) process estimated using the Case-Shiller index annual growth rate. Since the one-step-ahead forecasts of an AR(2) process is only a function of θ_1, each specification implies the same one-year forecast. The long-run predictions of a model can be summarized by its long-run persistence (LRP). When considering annual data (see Table 1.7 in Appendix 1.9), the LRP estimate range from the 1.5 (as estimated by the AIC model) to 2.8 (as estimated with the *intuitive* model). As Table 1.7 displays, there is a substantial degree of uncertainty around the estimated LRP. To capture this uncertainty, we consider specifications for process in (1.3) such that their LRP ranges between 1.4 and 4.5. The values of LRP in this range pin down the different values of θ_2. Finally, the parameter σ is set to such that all specifications imply a constant standard deviation equal to the estimated value from Case-Shiller index annual growth rate (0.049). This approach allows us to isolate the effects of a change in the perceived persistence of the house price growth rate process from changes in its perceived unconditional variance. Table 1.4 reports the resulting calibration for six specifications of the model in equation (1.2) among the 50 that we consider in our simulation, together with the implied long-run persistence.

Table 1.4: Calibration of some processes

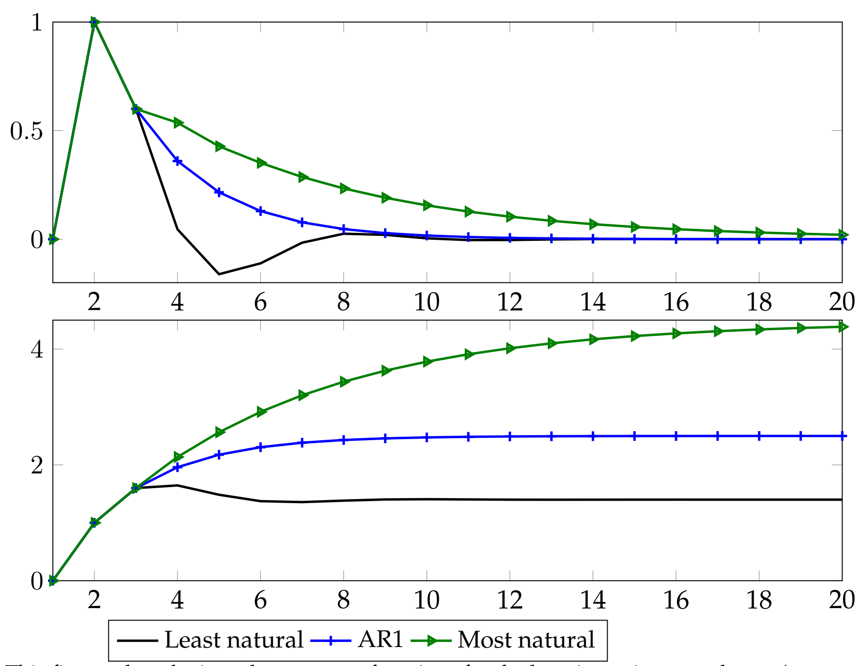
Process	LRP	θ_1	θ_2	σ
1	1.4	0.6	-0.31	0.041
10	1.93	0.6	-0.12	0.041
20	2.51	0.6	0.002	0.039
30	3.10	0.6	0.08	0.037
40	3.73	0.6	0.13	0.035
50	4.48	0.6	0.18	0.033

Note: This table reports the long-run persistence (LRP), the two autoregressive parameters (θ_1 and θ_2) and the standard deviation (σ) for six out of the 50 specifications of model as in (1.2).

Notice that the degree of *naturalness* of an agent is driven by the second order autoregressive parameter, θ_2: when this parameter is negative, agents are not *natural* since they expect a long-run mean reversion of housing prices after a positive short-run momentum; when θ_2 is positive, agents are *natural* since they expect the short-run momentum to persist in the long-run.

Figure 1.6 displays the impulse response functions and their cumulative values for three of the above-described processes. More precisely, we plot the IRFs and CIRFs of the AR(1) process (cross-line), as a reference, along with the two "extreme"' processes: process 1 (solid line) representing the process with the lowest degree of *naturalness* and which accordingly displays the strongest long-run mean reversion; process 50 (triangle-line) representing the process with highest degree of *naturalness*. Notice that the forecasted long-run price by process 50 is almost double the one implied by an AR(1) process.

Figure 1.6: IRFs and CIRFs for selected processes



Note: This figure plots the impulse response functions for the housing price growth rate (top-panel) and level (bottom panel) for three different processes used to solve the model: the one characterizing the most natural agents (green-triangle line), the AR1 model (blue-star line), and the one characterizing the least natural agents (black-solid line).

Calibration of Structural Parameters

The calibrated structural parameters of the model and their values are reported in Table 1.5.

Table 1.5: Calibration of structural parameters

Parameter	Value	Description
β, δ	0.98	Discount rate for household and banks
h	1.5	Housing stock
η	2	CRRA coefficient
y	1	Income per year
γ	5%	Rental rate as a fraction of house value
κ	20%	Collateral value for the bank as a fraction of house value

We set the discount rate for both the household and the bank at 0.98, which is consistent with an annual risk-free rate of 2 percent. The housing stock, h, can be interpreted as the housing value in the initial period, since we set the initial housing price p equal to one. Hence, h relates to the housing value to income in 2000. This value is equal to 2.1 in the Survey of Consumer Finance data, whereas it is equal to 1.3 when considering national aggregate data. Hence, we set h to be equal to the intermediate value of 1.5. We assume a constant relative risk aversion (CRRA) utility function, i.e. $u(c) = \frac{c^{1-\eta}-1}{1-\eta}$, with coefficient of risk aversion η equal to 2, a value broadly in line with the literature. Annual income, y, is standardized at the level of 1. We assume that the rental rate, γ, is 5 percent of the current value of the housing stock, thus implying a price-to-rent ratio equal to 0.05, which is consistent with the setting in Garner and Verbrugge (2009) and in Hu (2005). Finally, we assume that when the household defaults, the bank is able to recover only 20 percent of the value of the house. Such a value is in line with our interpretation of the asset in the economy as an HELOC.[27]

1.6 Quantitative Effects of Natural Expectations

Given the calibration of the structural parameters, the 50 specifications of the housing price growth process used by agents to forecast future housing prices, and the realized evolution of housing price for the 10 periods, as

[27]Since HELOCs are junior-liens, and the maximum loan-to-value ratio for a first-lien is 80 percent, we are then implicitly assuming that the bank is able to fully recover the value of the equity in the house sale.

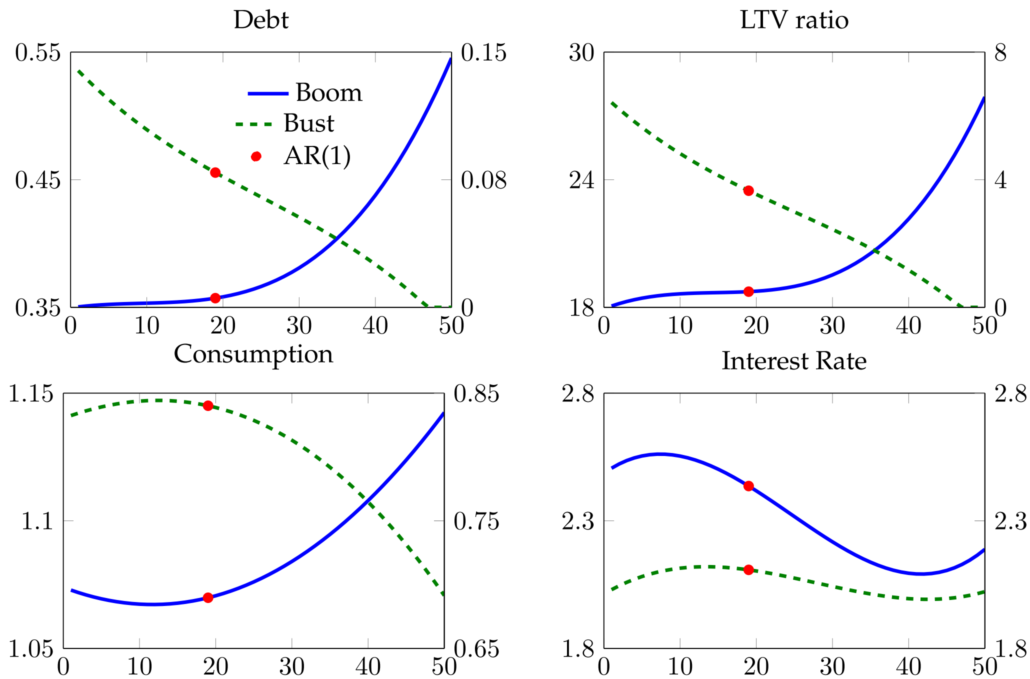
shown in Figure 1.5, we can compute the equilibrium dynamics of the variables of the model. Specifically, we are interested in the debt-to-income ratio, $\frac{d}{y}$, the consumption-to-income ratio, $\frac{c}{y}$, the loan-to-value ratio, $\frac{d}{ph}$, and the interest rate associated with home equity loans, r_t. We now investigate how these variables vary with agents' *naturalness* in the housing price boom and bust, separately.

Equilibrium in a boom

Figure 1.7 reports the average values of debt (upper left panel), LTV ratio (upper right panel), consumption (lower left panel) and interest rate (lower right panel) for each of the 50 specifications of expected housing price growth (x-axis) across the boom phase (from period 1 to period 6 in our model, which corresponds to the period 2000-2005 in the data, blue solid line) and across the bust (from period 7 to period 9 in our model, which corresponds to the period 2007-2009 in the data, green dashed line). As a reference point, we denote with a red circle the values associated with assuming the agents form expectations using an $AR(1)$ process, which relates to the *intuitive* statistical model as presented in Section 1.3. First, we consider the average values of our variables of interest during the boom phase.

Four results are worth highlighting. First, the model predicts a positive relationship between the average equilibrium level of debt in the economy in the boom phase and the degree of *naturalness* of agents. Recall that the 50 specifications for the expectations range from higher ability of the model to incorporate long-run mean reversion (specification 1, low *naturalness*) to lower ability of the model to incorporate long-run mean reversion (specification 50, high *naturalness*). Intuitively, after observing an increase in the housing prices, a more *natural* agent expects a longer-lasting appreciation of housing prices, which gives higher incentive to demand/supply debt. In contrast, a less *natural* agent expects a short-run momentum in housing prices followed by a mean reversion adjustment after some periods, as it can be visualized by the impulse response function for specification 1 in Figure 1.6. As a result, the household is less willing to demand debt and the bank is less willing to supply it. A second important result relates to the role of long-run expectations. Notice when agents in the economy are characterized by the lowest degree of *naturalness*, the equilibrium level of debt is roughly 35 percent of income. In contrast, when the agents ignore hump-shaped dynamics of housing prices, the equilibrium level of debt in the economy escalates to 55 percent of income. We obtain a similar pattern when considering the loan-to-value ratio, which increases from 18 percent for the least *natural*

Figure 1.7: Boom and bust dynamics for selected processes



Note: This figure displays the average values of debt-to-income (upper left panel), LTV ratio (upper right panel), consumption-to-income (lower left panel) and interest rate (lower right panel) for each of the fifty specifications of expected house price growth. The values displayed in the figure have been interpolated by a 3rd degree polynomial. The x-axis reports the number of each process, from the least (process 1) to the most (process 50) *natural*. Average values are computed both across the boom phase (from period 1 to period 6 in our model, which correspond to the period 2000-2006 in the data, blue solid line) and across the bust (from period 7 to period 9 in our model, which corresponds to the period 2007-2009 in the data, green dashed line). The red nodes in each panel represents the level of debt of the AR(1) process.

agents to 28 percent for the most *natural* agents. The pronounced differences in these quantities is solely due to the contrasting long-run expectations of housing prices, since by construction agents have the same short-run expectations in each of the 50 specifications. These results strongly support the argument in Case et al. (2012): the role of homebuyers' long-run housing price expectations is a crucial determinant of agents' behavior in terms of the consumption/saving choice. As a third result, notice that the accumulation of debt fuels consumption in the short-run, since there is positive correlation among average consumption in a boom phase and the degree of *naturalness* of agents in the economy. Intuitively, when expecting higher future appreciation of house's price, the resulting wealth effect provides incentives to consume in the current period. As a forth result, notice that debt is associated with a lower interest rate in economies where agents are more *natural*. Intuitively, since banks in the model share the same form of expectations of households, when banks expect both short-run and long-run momentum in housing prices, they are willing to lend at a lower equilibrium price.

The above findings can be summarized as follows: when housing prices start to increase, a *natural* agent (a household or a bank) overestimates the persistence of positive shocks and ignores the possible long-run mean reversion that follows a short-run momentum. As a consequence, the household or bank also overestimates the overall long-run appreciation of the housing stock. Given the availability of financial instruments to smooth future housing wealth, a *natural* household has, then, more incentive to extract a large portion of home equity to increase its consumption immediately. A *natural* bank will then be willing to provide loans to the household at lower price. As a result, *natural* expectations leads to large leverage during a housing price boom.

Equilibrium in a bust

The second set of results concerns the adjustment that the economy makes during the house price bust (periods from 6 to 9). These results reflect the predictions of our model for the behavior of agents in the period 2007-2009 and they show that the relationships between debt, consumption and degree of *naturalness* described above for the boom period are reversed. More *natural* households deleverage their debt position and they drastically reduce their consumption. Specifically, in the economies with most *natural* agents (processes 47-50), the amount of debt the household is able to extract is null.[28] Although quite drastic, this result is in line with evidence regarding the practice of HELOC freezes observed since 2008, when financial institutions realized the depth of the bust (WSJ, 2008). Notice that the adjustment if households were less *natural* households would be less sharp: they reduce their consumption to a lower degree and they are still allowed to borrow to smooth consumption, since they have previously accumulated relatively low levels of debt during the boom phase.

[28]Such sharp dynamics in the deleveraging process may be due to the absence of frictions (e.g. adjustment costs) in lending: in case of an abrupt decline in collateral values, banks in our model suddenly cut-off lending. However, note that in the above calibration in equilibrium the household never reaches the default region.

The role of bank's expectations

In Section 1.2 we documented that financial experts are likely to have held *natural* expectations during the housing price boom of the early 2000s, since their forecast do not show any long-run mean reversion after the short-run momentum. Since our theoretical model accounts for both the demand and supply of credit, we can now assess the impact of debt-supply *naturalness* on macroeconomic variables of interest. Specifically, we now perform some experiments to identify the contribution of banks' and households' expectations on the equilibrium outcome of debt and interest rate under the following four competing hypotheses: (a) both the bank and the household hold strongly *natural* expectations; (b) the bank and the household do not hold *natural* expectations; (c) only the household is strongly *natural*, while the bank is not; (d) only the bank is strongly *natural*, while the household is not. In these experiments, for simplicity, we give the *natural* label to an agent that forecasts future housing prices using the most *natural* process (process 50), and we give the *non-natural* label to an agent that forecasts future housing prices using the least *natural* process (process 1). These extreme values are vehicles for understanding the role of expectations in regards to supply and demand. Table 1.6 displays the results.

Table 1.6: Debt dynamics under different assumptions

	Boom		Bust	
	Debt	Rate	Debt	Rate
a) Bank and Household natural	54.5	2.2	0.0	-
b) None natural	35.0	2.5	13.9	2.0
c) Only Household natural	36.2	2.8	9.2	2.1
d) Only Bank natural	42.2	2.1	5.1	2.0

Note: This table reports the simulated average level of debt and interest rate across the boom phase (left panel, from period 1 to period 6 in our model, which correspond to the period 2000-2006) and bust phase (right panel, from period 1 to period 6 in our model, which correspond to the period 2000-2006 in the data) under the hypothesis that both the bank and household are natural (a), both bank and household are not natural (b), only the household is natural (c), and only the bank is natural (d). In this exercise, for simplicity, we assume that a natural agent uses process 50 to make forecasts, whereas a non natural agent uses process 1.

The most striking result of our experiment reflects the crucial importance of banks' expectations for the equilibrium level of debt. Let's analyze first the boom phase. When both agents are not *natural*, as in scenario (b), the equilibrium level of debt in the economy is relatively low (around 35 percent of income). If we assume that only the household is *natural*, as in scenario (c), the equilibrium level of debt increases by only 5 percent, whereas if only the bank is *natural*, as in scenario (d), the equilibrium level of debt increases up to 48 percent. In other words, without assuming a bank expectation channel, a model in which only households are natural can only replicate a small portion of the leverage level in the economy during the house price boom. The intuition for this result stems from the fact that default in our model is a cost for households but a revenue for the bank and this cost/revenue is increasing in the expected housing price. Hence, the feature of the model that allows banks to seize a fraction of the households' housing stock, a rather realistic assumption, makes the debt supply's schedule particularly sensitive to financial intermediaries' long-run expectation about housing prices.

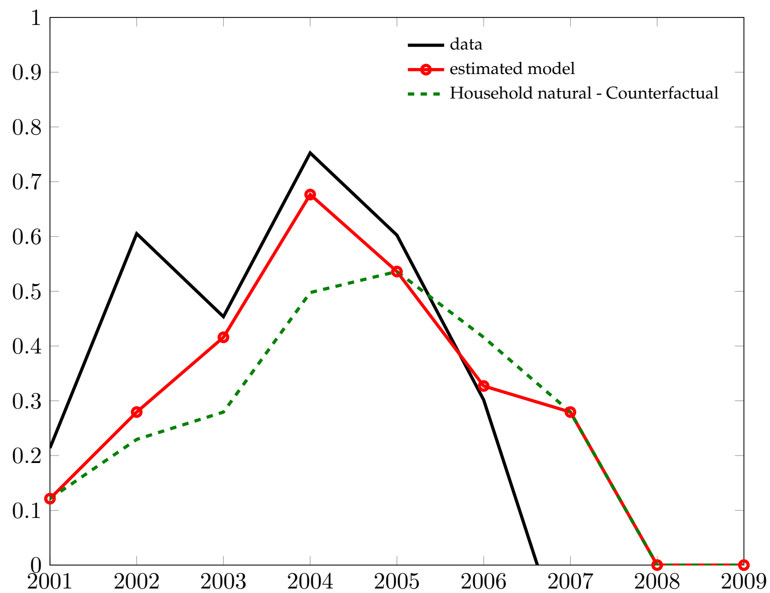
Estimating Naturalness from the Data

Finally, we perform a comparison of our simulations with the debt-dynamics observed in the data to pin down which degree of *naturalness* better fits the debt data. The first step is to obtain a series that is comparable to the debt-to-income ratio as simulated in our model. We first consider the annualized series of Gross Home Equity Extraction in the U.S., as in Greenspan and Kennedy (2005).[29] The series is available only until to 2008Q4. We divide the series by nominal disposable personal income to compute the debt-to-income ratio. Because the series is not directly comparable to the outcome of our simulated model, we need to correct the former for the fraction of households effectively extracting home equity. Therefore, we make use of the Survey of Consumer Finance data to compute the fraction of households with an outstanding HELOC and interpolate via cubic splines for the years in which the survey is not available. Such a percentage varies from 2.7 per cent in 2001 to 4.6 per cent in 2008. We then compare the resulting debt-to-income series with the debt dynamics of the model (where both household and bank can be natural) across the 50 specifications and we select the process whose debt dynamics minimize the Euclidean distance with the data. Figure 1.8 plots the selected process (black solid line) and the debt-to-income ratio in the data (red circled line). The selected specification is process 31, a fairly persistent and *natural* one, since its second order autoregressive parameter is positive, $\theta_2 = 0.08$, and its LRP is fairly large, equal to 3.15. Notice that the implied LRP is even higher that the one estimated on yearly data with the *intuitive* model (se Table 1.7 in Appendix 1.9). To remark the importance of bank's naturalness, in the same figure we plot the simulated path of debt under the

[29] The series is the sum of (a) cash-outs resulting from refinancings, (b) originations to finance purchases of existing homes minus sellers' debt cancellation, and (c) changes in home equity debt outstanding less unscheduled repayments on regular mortgage debt outstanding.

scenario in which only the household is natural (its expectation follow the estimated process 31) and the bank is not natural (its expectation follows the least natural process 1). It can be observed that in order to closely match the data having a *natural* household is not enough: we need a significant degree of naturalness both on the household and on the bank side.

Figure 1.8: Actual v. simulated data



Note: The black solid line in this figure displays the ratio of gross Home Equity Extraction over Personal Disposable Income, weighted by the fraction of households with an active HELOC (source: Survey of Consumer Finance). The y-axis (debt to income ratio) is measured as absolute deviation from 2000 (which corresponds to our initial date $t = 0$ in the model). The red circled line is the simulated debt path arising from process 31, which is the process that minimize the Euclidian distance between the data and the dynamics of debt predicted by our model when varying the degree of naturalness of the agents (process 1 to 50). The green-dashed line represents the debt dynamics under the assumption that only the household is natural (process 31) but the bank is not natural (process 1). Sources: Greenspan and Kennedy (2005), FRED, Federal Reserve Economic Data, Federal Reserve Bank of St. Louis and SCF.

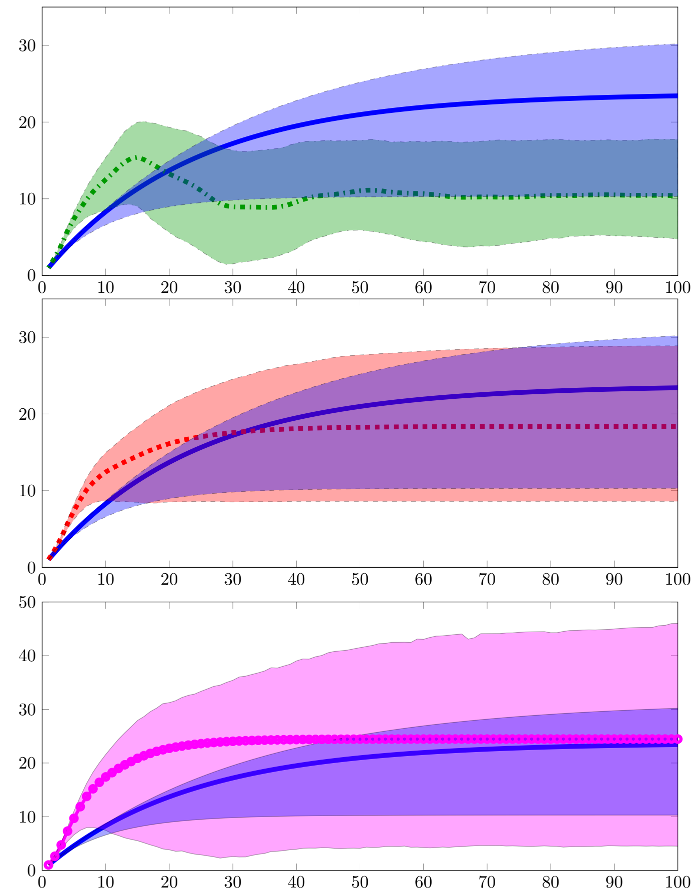
1.7 Conclusion

The recent financial crisis has served as a reminder of the potential danger caused by undisciplined collateralized debt markets. In this paper, we use home equity extraction as a case study to explore the distortions arising from *natural* expectations about future values of collateral. We show that *natural* expectations arose during the period of the recent housing price boom because of the failure of households and financial experts to take into account the complex structure of house prices. We show that agents may end up overestimating long-run prices if they make use of models that fail to capture the rich autocorrelation structure of housing prices and its mean-reverting component. While the notion that households are likely to misestimate house prices has been documented in the literature, in this paper we provide evidence that financial experts also were too optimistic about long-run prices before and during the recent house price boom. Specifically, out-of-sample forecasts gathered from a professional forecaster largely overestimated long-run prices and did not capture any long-run mean reversion after the positive short-run momentum. We show the quantitative implications of *natural* expectations in a model where households and banks interact through a collateralized financial instrument. We feed the model with a set of expectations that differ in their ability to capture hump-shaped housing price dynamics. We document that after a positive shock on housing prices, less *natural* agents expect a lower persistence of the shock. In contrast, natural agents overestimate the persistence of the process, thus leading to overly optimistic long-run forecasts. We then simulate the model by considering housing price dynamics as observed during the 2000s. Our models predict a positive relationship between the amount of home equity extracted in a boom phase and the degree of *naturalness* of the agents in the credit market, while at the same time stressing the prominence of banks' expectations in the equilibrium outcome. A version of the model in which agents hold *natural* expectations seems to captures the dynamics of U.S. home equity extraction during the recent boom and bust relatively well. Finally, we highlight that financial experts *naturalness* is a crucial component for observing a large accumulation of debt at low interest rates.

1.8 Appendix: Confidence Band Impulse Response House Price

The top panel of Figure 1.9 plots together the level impulse response of the *intuitive* model (blue solid line) and the AIC model (green dotted line) and their 95 percent confidence band (shaded area); the central panel plots together the level impulse response of the *intuitive* model (blue solid line) and the BIC model (red dashed line) and their 95 percent confidence band; and the bottom panel plots together the level impulse response of the *intuitive* model (blue solid line) and the *finite memory* model (purple circled line) and their 95 percent confidence band. As expected, the uncertainty around the impulse responses is large and the confidence bands largely overlap.

Figure 1.9: Impulse Response Functions with confidence bands



Note: This figure reports the cumulative impulse response function (CIRF) of house price growth rate to a positive unitary shock. Shaded areas represent the 95 per cent confidence intervals. Top panel: intuitive model (blue solid line) and AIC model (green dotted line). Central panel: intuitive model (blue solid line) and BIC model (red dashed line). Bottom panel: intuitive model (blue solid line) and finite memory model (purple circled line).

1.9 Appendix: Long-Run Price for Annual Data

Table 1.7: LRP and Confidence Band

	Natural	BIC	AIC	Short Memory
p	1	6	7	2
Long-Run Persistence (LRP)	2.76	1.72	1.52	2.29
Confidence Bands (95%)	[2.17;4.49]	[0.85;3.05]	[0.67; 2.91]	[0.25; 5.17]

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Chapter 2

Noisy Fiscal Policy

2.1 Introduction

A recent stream of literature has investigated the role of foresight in fiscal policy, which implies that the implementation of fiscal policy measures is lagged with respect to their announcement (see, e.g., Leeper, Walker, and Yang, 2013). This literature is concerned with the macroeconomic effects implied by the presence of fiscal policy news. For example, Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012) and Born, Peter, and Pfeifer (2013) find that news shocks explain a major portion of government spending fluctuations. Moreover, these studies find that news on government spending propagates significantly through the real economy: if one abstracts from other sources of aggregate fluctuations and considers government spending shocks in isolation, the expected components of government policies (i.e., news shocks) account for between 40% and 100% of the variance of GDP, and the remaining variance is attributable to unexpected government spending shocks.

News shocks are introduced in this literature by assuming that agents have perfect foresight about the size and the timing of future policy. However, recent influential contributions in macroeconomics have highlighted the role of imperfect information in business cycles. In particular, such findings are found in Lorenzoni (2009), which shows that imperfect information about aggregate productivity is a key source of cyclical fluctuation.

Given the considerable uncertainty surrounding the implementation of fiscal policy, it seems natural to extend the setup to imperfect information about news to the case of government spending. In this paper, we thus focus on the macroeconomic effects of noisy fiscal policy announcements. By noisy announcements, we mean the following: A policymaker announces a fiscal policy measure at a particular point in time that is supposed to come into effect at a future date, while private agents in the economy believe that the announcement may not be fully implemented. Partial implementation may be due to amendments that occur during the legislative process or to incomplete information about future states of the economy. As a consequence, the information structure we examine is different from previous papers in which future fiscal policy is fully predictable.

Thus, the main contribution of this paper is twofold: i) we quantify the size of noisy news using data from both forecasts and realizations of government spending; ii) we assess the effect of noise and its propagation through the economy using a medium-scale DSGE model with real frictions.

The main result of this paper is that a "noisy" announcement leads to an under-reaction of macroeconomic variables to the announcement itself. The values of the fiscal multipliers drastically fall compared to the full information case. We make use of the official government spending forecasts from the annual budgets of three countries (Canada, the United Kingdom and the United States) for which we were able to obtain enough information. We find that the amount of noise observed for these three countries is rather significant: the share of noise in these official government spending forecasts ranges from 28% in the US to 84% in the UK. When embedding these estimates into a full-fledged DSGE model, we find that in a "noisy" scenario, before news events are realized, the value of government spending multipliers, compared to the full information case, falls proportionally to the level of noise. Additionally, the effect of noise does not vanish with the occurrence of the fiscal shock. For example, in the UK, for which the relevance of noise is most compelling, we obtain a loss in the output multiplier of approximately 10% one year after the materialization of the news compared to the perfect information case. Such an effect is more pronounced for investment, even in economies in which the role of noise is limited; for example, for the US, which is the country with the lowest share of noise among those considered, we find that the loss in the investment multiplier one year after the realization of a news event remains at approximately 12%, a non-negligible figure.

Our work can thus be seen as an attempt to connect several bodies of literature. First, our paper is an extension of the literature on fiscal foresight. Notably, papers such as Ramey (2011) and Leeper, Walker, and Yang (2013) show the relevance of fiscal foresight and the perils econometricians face from ignoring it.[1] Such findings have been recently reinforced by Born, Peter, and

[1] An earlier attempt to introduce anticipated fiscal policy in an SVAR framework can be

Pfeifer (2013), which shows that all of the output variance generated by fiscal policies arises from news about government spending. We show that when imperfect information is included, the effects of fiscal foresight are drastically reduced.[2]

Other studies (Ellahie and Ricco, 2014; Ricco, 2014) introduce informational frictions in SVAR models, although no microfoundations for such frictions are provided. In particular, Ricco (2014) introduces a shock to agents' expectations, a so-called "misexpectation shock", into a rather standard fiscal VAR model. Such a shock is aimed at capturing "the differences between the agents' expectations about the current state of the economy and the ex-post revealed value of macroeconomic variables" (Ricco 2014, p.4). This shock is due to information frictions. The author finds that macroeconomic variables react to such shocks, albeit more moderately than to fundamental fiscal shocks. In our paper, we recover similar findings and provide a structural interpretation of agents' misexpectations.

Our approach is also partly related to a set of papers on fiscal policy uncertainty. One of these papers recently revived interest in fiscal uncertainty, Bloom, Baker, and Davis (2013), which empirically demonstrates the detrimental effects of fiscal uncertainty on macroeconomic variables. Fernández-Villaverde et al. (2011) instead develops a model in which the volatility of fiscal policy is assumed to be changing over time. Such a feature of fiscal policy leads to an increase in uncertainty and implies detrimental effects on both output and consumption. When monetary policy is stuck at the zero lower bound, such effects are reinforced. These findings are also shown in a New Keynesian model by Johannsen (2014). There are, however, three main differences between this strand of literature and our approach. First, from a methodological point of view, we provide a structural interpretation of fiscal uncertainty (i.e., for the lack of full information), whereas in the above-mentioned papers, uncertainty is modeled as an exogenous time variation in the volatility of model disturbances. Second, we focus on government spending rather than on taxes because introducing (distortionary) taxes would make our arguments slightly more opaque and because of the

found in Tenhofen and Wolff (2007).

[2]A slightly different approach is pursued in Hollmayr and Matthes (2015), wherein uncertainty stems from the fact that agents learn whether shocks are temporary or permanent over time. This, of course, leads to an increase in the volatility of the macro variables over the short run compared with the case in which agents perfectly know the nature of the shock that is affecting the economy. A similar result can be found in our paper when the economy experiences a permanent fiscal shock. For a model of fiscal consolidation in which agents need to learn whether restrictive fiscal shocks are temporary or permanent over time, see Lemoine and Lindé (2015).

lower comparability of tax schedules across countries.[3] Third, the detrimental effects of uncertainty obtained in the above-mentioned papers are mainly related to precautionary savings motives that arise from the time-varying nature of the shocks' volatility. In the current paper, we instead focus on the first-order effects of uncertainty.

The idea that noise pollutes the impact of news shocks is not new in macroeconomics. Indeed, a recent stream of literature has highlighted the problems with the identification of these two shocks, although the focus of this literature is on TFP shocks (Blanchard, L'Huillier, and Lorenzoni, 2013; Barsky and Sims, 2012 and Forni et al., 2014). With respect to this literature, our contribution is related not only to the introduction of noise in government spending but also to the identification procedure, which relies on the comparison of forecasts and realizations of the government spending process.

This paper proceeds as follows. In Section 2.2, we introduce the quantitative model and highlight its key items. In Section 2.3, we introduce our empirical methodology, while in Section 2.4, we estimate the amount of news and noise in the data. In Section 2.5, the results of the quantitative exercise are shown and discussed. Finally, Section 2.6 concludes.

2.2 The model

To investigate the quantitative properties of noisy fiscal policy we rely on a model with real frictions, along the lines of Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012). The main features of the model are described in the following sections.

Household and firm

There is a representative household maximizing

$$\hat{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{m_t^{1-\sigma}}{1-\sigma} - \omega \frac{n_t^{1+\kappa}}{1+\kappa} z_t^{1-\sigma} \right],$$

where $\beta \in (0,1)$ is the discount factor, $\sigma > 0$ is a parameter governing the elasticity of intertemporal substitution ($\frac{1}{\sigma}$), $\omega > 0$ is a scale parameter, and $\kappa \geq 0$ is the inverse of the Frisch elasticity of labor supply.

[3] In an extension of our model (available upon request) with distortionary taxes on capital, we show that an announced increase in taxes on capital negatively affects both output and consumption. However, contrary to Fernández-Villaverde et al. (2011), the lack of information on news shocks in our model mitigates this negative effect.

The variable z_t is an exogenous, deterministic process representing a labor augmenting technology that evolves according to

$$z_t = \gamma_z z_{t-1}.$$

The variable n_t represents hours worked, while m_t is a composite good made of both durable and nondurable goods

$$m_t = c_t^{\nu} v_t^{1-\nu} - b c_{t-1}^{\nu} v_{t-1}^{1-\nu},$$

where c_t and v_t are non-durable and durable goods, respectively, and $\nu \in [0, 1]$ is a share parameter.

In each period the household budget constraint writes

$$c_t + x_t + d_t = w_t n_t + r_t u_t k_t + T_t,$$

where x_t and d_t are new purchases of capital and of durable goods, respectively.[4] Real wages are denoted w_t, returns on capital r_t and capital utilization u_t. Taxes T_t are levied in a lump-sum fashion. The respective laws of motion of capital and of durable goods are given by

$$k_{t+1} = [1 - \delta_k - \Psi_k (u_t)] k_t + x_t \left[1 - \Phi_k \left(\frac{x_t}{x_{t-1}} \right) \right]$$

and

$$v_{t+1} = (1 - \delta_v) v_t + d_t \left[1 - \Phi_v \left(\frac{d_t}{d_{t-1}} \right) \right].$$

We assume that Φ_k, Φ_v and Ψ are zero at the non-stochastic steady state and that Φ_k', Φ_v', Φ_k'', Φ_v'' and Ψ' are greater than or equal to zero.[5]

The firm maximizes its profits under a standard Cobb-Douglas production function

$$\begin{aligned} & \max_{n_t, k_t} y_t - w_t n_t - r_t u_t k_t \\ s.t. \quad & y_t = a (u_t k_t)^{\theta} (z_t n_t)^{1-\theta}. \end{aligned}$$

Given that the focus of this paper is on government spending shocks, we keep – without loss of generality – TFP, denoted a, fixed.

[4] In our model, durable goods do not play a specific role. We introduce them to keep our model as in line as possible with Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012).

[5] The functional forms we choose are $\Phi_k = \frac{\omega_i}{2} \gamma_z^2 \left(\frac{x_t}{x_{t-1}} - 1 \right)^2$, $\Phi_d = \frac{\omega_d}{2} \gamma_z^2 \left(\frac{d_t}{d_{t-1}} - 1 \right)^2$, and $\Psi = \psi_1 (\nu_t - 1) + \frac{\psi_2}{2} (\nu_t - 1)^2$.

Government sector

The government budget is assumed to be balanced (i.e., $T_t = g_t$), with a government spending process that is exogenous and driven by news.[6] The process can be then written (in log-deviations from the steady state) as

$$\widehat{g}_t = \rho \widehat{g}_{t-1} + \varepsilon_{t-q} \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{2.1}$$

where $|\rho| \leq 1$, and ε_t is a white noise shock to government spending with mean zero and variance equal to σ_ε^2. The exogenous fiscal policy shock is a news shock that appears with a lag equal to q periods.

Notice that government spending is modeled as a rather persistent AR(1) process. This modeling choice replicates the findings of several estimated DSGE models, where the autoregressive parameter for government spending found is very close to unity (e.g., Smets and Wouters (2007), Mertens and Ravn (2011), Khan and Tsoukalas (2012) and Schmitt-Grohé and Uribe (2012)), and is reinforced by the findings discussed in Section 2.3.

For sake of simplicity, we focus here on the case with a single news shock to government spending. More general representations (including multiple news shocks) are discussed in Leeper et al. (2013) and Beaudry and Portier (2014).[7]

Let us assume for simplicity that $q = 1$. Then, the timing of the shock is such that the new policy is known one period in advance. Such timing is used to illustrate the presence of noisy news. We will relax this assumption later by considering longer lags in the announced government spending policy and a more complex information structure. The new government policy expected in period $t+1$ is then given by

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \hat{E}_t \varepsilon_t.$$

If the change in government spending is perfectly anticipated by private agents, this equation reduces to

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \varepsilon_t \equiv \widehat{g}_{t+1}.$$

Thus, the expected change in government policy, represented by a news shock, is perfectly forecasted by private agents, i.e., they know the new government policy in advance. Here, we depart from this setup by assuming that

[6] As Ricardian equivalence holds in this setup, one could also introduce government debt, with the results being unaffected.

[7] See also, the discussion about identification with multiple news events in the next section.

private agents observe a noisy signal of ε_t (i.e., noisy news about government spending) from

$$s_t = \varepsilon_t + \nu_t, \tag{2.2}$$

where ν_t represents a noise shock. This variable is assumed to be a zero mean white noise with variance σ_ν^2, and it is uncorrelated with ε_t for any time index. If the endogenous variables of the model react to noise, then the economy displays sunspot-like fluctuations, as it is affected by shocks that are unrelated to fundamentals. This noise shock is of central interest in the following sections. It represents how the private sector anticipates the way that government policy is conducted.

Such noise is meant to capture the complex political process that leads to policy changes, as well as political economy considerations. For example, such a setting could capture a situation wherein a policymaker announces measures that can be partially eliminated during the legislative process (for example, because of a different majority in parliament).

If the volatility of ν_t is negligible with respect to ε_t, private agents would react immediately to news in the government policy. In this case, the private sector perfectly foresees how an announced government spending policy will be conducted. If the signal is noisy, this is no longer the case. Indeed, expectations of the new policy are corrupted because private agents do not react perfectly to the announcement about government spending in such an environment.

In this imperfect information case, the conditional expectations of private agents are given by

$$\hat{E}_t \varepsilon_t = \alpha s_t \equiv \alpha \left(\varepsilon_t + \nu_t \right),$$

where the parameter α is obtained from a linear projection of ε_t on s_t (see Hamilton 1994a)

$$\alpha = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\nu^2}.$$

When information is perfectly transmitted to private agents in the economy ($\alpha = 1$ and $\sigma_\nu = 0$), they fully incorporate the announced government policy in the next period, so they can immediately adjust their consumption and labor supply decisions to the new economic conditions. Conversely, when the announced policy is completely noisy ($\sigma_\varepsilon / \sigma_\nu \to 0$ and $\alpha \to 0$), they will not react, as their expectations are insensitive to the new policy.

Before calibrating and solving the model, we describe the methodology used to extract both news and noise from the data, we then discuss the results of our estimation.

2.3 Identifying news and noise from government spending forecasts

In this section, we will discuss our empirical methodology for recovering the relative contributions of news and noise using both realizations and expectations of government spending. Instead of using a full information estimation technique that requires us to solve and estimate a DSGE model with noisy news shocks and other disturbances, we propose a simple limited information approach that only exploits data for actual realizations and forecasts of government spending. In addition to its simplicity, an advantage of this procedure is that the estimation does not depend on the specification of the whole DSGE model. As most of the data we consider are available at an annual frequency, we will also propose a method to recover the parameters at a quarterly frequency.

Methodology

The methodology we rely on for recovering α is an application of the method of moments, with targeted moments being derived by comparing the agents' forecasts and actual government spending.

To start, assume that government spending obeys process (2.1) with $q \geq 1$. Also suppose that agents observe $\widehat{g}_t$ and a signal as in (2.2) from which they infer the value of ε_t. Regardless of the value of q, the econometrician has enough information to estimate ρ and σ_ε^2 from the observation of $\widehat{g}_t$.

Additionally, the agents' forecasts will be

$$\hat{E}_t \widehat{g}_{t+1} = \rho \widehat{g}_t + \hat{E}_t \left[\varepsilon_{t-q+1} | S_t \right] \equiv \rho \widehat{g}_t + \alpha s_{t-q+1},$$

where

$$\alpha = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\nu^2}$$

and

$$S_t = \{ s_t, s_{t-1,\ldots} \} .$$

We can then make use of these forecasts to estimate the variance of noise by computing the one-period-ahead forecast net of the autoregressive component

$$\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t = \alpha \left(\varepsilon_{t-q+1} + \nu_{t-q+1} \right) \tag{2.3}$$

and then taking the variance of such an object

$$V_1 \equiv V \left(\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t \right) = \alpha^2 \left(\sigma_\varepsilon^2 + \sigma_\nu^2 \right) = \frac{\sigma_\varepsilon^4}{\sigma_\varepsilon^2 + \sigma_\nu^2} \tag{2.4}$$

from which we derive σ_ν^2

$$\sigma_\nu^2 = \frac{\sigma_\varepsilon^2 \left(\sigma_\varepsilon^2 - V_1\right)}{V_1}.$$

From the inspection of (2.4), notice that $\sigma_\varepsilon^2 > V_1$. Note that this moment does not depend on the lag q of the announcement: this property allows us to recover α.[8] Once we have α and ε_t, we can directly recover the noise ν_t from (2.3).

An equivalent way to estimate α relies on performing a linear projection of the forecast error in (2.3) on the realization of the shock $\widehat{g}_{t+1} - \rho\widehat{g}_t = \varepsilon_{t-q+1}$

$$\frac{Cov\left(\varepsilon_t, \alpha s_t\right)}{Var(\varepsilon_t)} = \alpha,$$

where the residual of this OLS regression of αs_t over ε_t is equal to $\alpha\nu_t$, so the time series of ν_t is also easily recovered. An interesting observation comes from the fact that the R^2 of the regression is equal to α. This means that when the signal is not very noisy (i.e., $\sigma_\nu \to 0$), a good inference can be made concerning the fundamentals of the economy. However, when the signal is extremely noisy (i.e., $\sigma_\nu \to \infty$), no inference can be made.

Discussion

Two remarks on the suggested methodology are in order. First, note that the above identification strategy crucially relies on the fact that the information set of the agents and that of the econometrician do not coincide. On the one hand, the econometrician does not directly observe the signal and therefore has to recover it indirectly from agents' expectations. On the other hand, the econometrician observes the future realizations from the actual government spending process, which are unknown data when the agents produce their forecasts. Hence, by comparing the outcome with the agents' forecasts, the econometrician is able to recover α.

Second, note that the estimation procedure for α can be polluted by model misspecification. We discuss three types of misspecification in the following paragraphs.

[8] We acknowledge, however, that this is not a general result. This property is obtained here because we consider a single news shock. With multiple news shocks and signals, the estimated α is polluted by the signals. See the discussion below.

Expected and unexpected fiscal shocks A first type of misspecification may arise if the true government spending process includes an expected and an unexpected component

$$\widehat{g}_t = \rho \widehat{g}_{t-1} + \epsilon_{t-q} + \eta_t,$$

with $\eta_t \sim N(0, \sigma_\eta^2)$. We will prove that ignoring the unexpected component of government spending leads to estimating an upper (lower) bound for the role of noise (news).

Suppose that the econometrician mistakenly ignores η_t and instead tries to estimate the model as in (2.1): she will then mistakenly treat the two shocks $\eta_t + \varepsilon_{t-q}$ as a single shock (denoted w_t). The variance of estimated news will be $\sigma_w^2 = \sigma_\eta^2 + \sigma_\varepsilon^2$. However the variance of the forecast, net of the autoregressive component, $\hat{E}_t \widehat{g}_{t+1} - \rho \widehat{g}_t = \alpha s_{t-q+1}$ is equal to $\alpha \sigma_\varepsilon^2$. Dividing this variance by the variance of estimated news yields the misestimated level of α

$$\tilde{\alpha} \equiv \frac{\alpha \sigma_\varepsilon^2}{\sigma_w^2} \equiv \alpha \frac{\sigma_\varepsilon^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} \leq \alpha,$$

where it can be seen that the lower the relative share of the expected component in government expenditure, the smaller the estimated α and the more relevant the misspecification bias.

Such misspecification, however, should not be troublesome in practice because Born, Peter, and Pfeifer (2013) show that the quantitative relevance of unexpected shocks to government spending is extremely limited, while almost all of its variance is due to expected shocks (and thus, $\tilde{\alpha}$ is very close to the true noise-to-signal ratio).

Multiple noisy news A different misspecification issue arises in if there are multiple noisy news. For clarity, we restrict our attention here to the case of two noisy news, although the argument can be easily made more general. Consider the government spending process

$$\hat{g}_t = \rho \hat{g}_{t-1} + \varepsilon_{1,t-1} + \varepsilon_{2,t-2},$$

where $\varepsilon_{1,t-1}$ and $\varepsilon_{2,t-1}$ have mean zero and variances $\sigma_{\varepsilon,1}^2$ and $\sigma_{\varepsilon,2}^2$, respectively. They are also uncorrelated. Private agents receive a noisy signal ($s_{1,t}$, $s_{2,t}$) for each news shock. The challenge here is to identify five parameters: ρ, $\sigma_{\varepsilon,1}$, $\sigma_{\varepsilon,2}$, α_1 and α_2 (or equivalently, $\sigma_{\nu,1}$ and $\sigma_{\nu,2}$). However, identifying all the parameters is not possible: our limited information approach has the advantage of being able to identify noisy news without specifying a whole model, but with the disadvantage that it uses too little information to estimate a richer specification of government spending. Identification can be achieved only if we impose some restrictions on the noise parameters.[9]

Also of interest is the case when the true model is composed of two noisy news shocks but the econometrician attempts to estimate the process as in (2.1). Direct computations yield

$$\tilde{\alpha} = \alpha_1 \omega + \alpha_2 (1 - \omega),$$

where

$$\omega = \frac{\sigma^2_{\varepsilon,1}}{\sigma^2_{\varepsilon,1} + \sigma^2_{\varepsilon,2}}$$

is the fraction of the variance of government spending explained by the news shock $\varepsilon_{1,t-1}$. It appears that our procedure correctly identifies the true noisy news if $\omega \to 1$ (i.e., the news shock $\varepsilon_{1,t-1}$ explains most of the variance of government spending) and/or $\alpha_1 \simeq \alpha_2$. Conversely, if the noisy structures are significantly different ($\alpha_1 \neq \alpha_2$) and the news shock $\varepsilon_{2,t-2}$ is the main driver ($\omega \to 0$), the procedure will correctly identify the value of α_2 but will fail to identify the true number of lags. However, note that the estimation results in Born, Peter, and Pfeifer (2013) indicate that among the news shocks, only the news shock with the longest delay matters, meaning that we can reasonably restrict our analysis to a single news shock.

Misspecification of the Autoregressive Process Thus far, we assumed that the AR(1) process for government spending is the true process. One may wonder how our estimate of α is affected by a misspecification of the autoregressive process. Let us then assume that the true data generating process (DGP) is an AR(2) process

$$\hat{g}_t = \rho_1 \hat{g}_{t-1} + \rho_2 \hat{g}_{t-2} + \varepsilon_{t-1},$$

where $\rho_1 + \rho_2 < 1$, $\rho_2 - \rho_1 < 1$ and $|\rho_2| < 1$ to satisfy stationarity conditions. Suppose that we wrongly assume that government spending follows an AR(1) process. Some tedious calculations[10] yield the estimated value of α in the misspecified AR(1) model under the true DGP

$$\widetilde{\alpha} = \mu_1 \left(\mu_0 + \alpha \right),$$

[9]For example, if we assume the same signal structure for both news processes ($\sigma^2_{\varepsilon,1} = \sigma^2_{\varepsilon,2} = \sigma^2_{\varepsilon}$ and $\sigma_{\nu,1} = \sigma_{\nu,2} = \sigma_{\nu,}$), then it is possible to retrieve the model parameters using our simple method of moments for realizations and expectations.

[10]See 2.7.

where

$$\mu_0 = \frac{\rho_2^2}{1-\rho_2^2};$$
$$\mu_1 = \left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho_1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho_1-\rho_2}{1-\rho_2}\right)\right).$$

The estimated value $\widetilde{\alpha}$ is a biased estimate of the true α unless $\rho_2 \neq 0$. When $\rho_2 \to 0$, $\mu_0 \to 0$ and $\mu_1 \to 1$, the bias tends to zero. There is no trivial characterization of this bias with respect to ρ_1 and ρ_2, but we can consider a simple illustrative example[11] that highlights the consequence of misspecification for the estimation of α. We set $\rho_1 = 0$, and then, ρ_2 can vary between -1 and 1. In this case, the estimation of α from the misspecified AR(1) model is given by

$$\widetilde{\alpha} = \rho_2^2 + (1-\rho_2^2)\alpha.$$

When $\rho_2 \to \pm 1$, the estimated value tends to one, and thus, we will incorrectly conclude that there is no noise in government spending policy. For any value of $\rho_2 \neq 0$, the estimation of the misspecified AR(1) model can yield $\widetilde{\alpha} > \alpha$; thus, we wrongly underestimate the size of the noise.

To address this misspecification issue, in what follows, we model government spending as an AR(1) process. As discussed, such a choice is not only in line with the literature but also with the evidence at our disposal. Indeed, if one takes the quarterly detrended log-series of real per capita government spending in the US (from 1952Q1 to 2014Q1), the AR(1) will be, among the ARMA(*p*,*q*) processes, selected using the Bayesian Information and Hannan-Quinn criteria.[12] The above evidence is also supported by the shape of the partial autocorrelation function, where the strong autocorrelation that emerges at a one-quarter lag suddenly disappears from two lags on, whereas the same function computed on Δg_t shows that this latter process has no significant autocorrelation at any lag (see Figure 2.9 in 2.8).

Recovering quarterly series

Most of the series we address are available at a yearly frequency, while most of the literature examines quarterly frequency data. Thus, a further step is

[11] See 2.7 for another illustration of misspecification.

[12] If one were to use the Akaike Information Criterion (AIC), the chosen process would be the ARMA(5,2). The AIC function, however, is very flat for processes with autoregressive parameters between 1 and 5. Additionally, the AIC results should be treated with caution given the well-known fact that this criterion is not consistent (see Lütkepohl 2005).

needed to convert our annual data into quarterly data. To do so, once the yearly parameters have been recovered, we make use of an indirect inference algorithm (Smith, 1993) to obtain comparable moments at a quarterly frequency.[13] The algorithm essentially generates simulated quarterly series for actual (with news) and expected (with news and noise) government spending whose moments, aggregated at a yearly frequency, yield the the same moments observed in the data. The outcome of the algorithm is a so-called "binding function" that links the α computed at a yearly frequency with parameters computed at a quarterly frequency. The function, reported in Figure 2.10 in 2.8, is increasing in both the autoregressive parameter and in the share of news in the signal. Note, however, that the higher the value of ρ, the flatter the function becomes in the value of α at an annual frequency. This implies that in such a case, two close annual estimates of α may lead to significantly different quarterly estimates of α.

In what follows, we apply the methodology described above to Canada, the United Kingdom and the United States.

2.4 Estimation results

In this section, we identify the relative importance of noise and news in the data, making use of the official government spending forecasts reported in the annual budgets of Canada, United Kingdom and United States as the primary data sources. For the US case, we also refer to another source of government spending forecasts, the Survey of Professional Forecasters (SPF), as a robustness check[14]. The output of our moments comparison exercise for these three countries is summarized in Table 2.1.

Canada

For Canada, we collect data from the annual federal budgets from 1968 to 2012. In Canada, the budget - which defines the budget plan for the next fiscal year (FY) - is usually presented to parliament between January and June. The FY in Canada starts on April 1st and ends on March, 31st of the next calendar year. The variable that we track was called "Budgetary Expenditures" until 1982. Since 1987, it has been called "Program Expenditures" (data from 1983 to 1986 are missing and have thus been interpolated via cubic splines). This

[13] Note that if we were to resort to usual temporal disaggregation techniques, we would obtain smooth time series in which the role of noise is significantly reduced.

[14] See 2.12 for the data sources.

Country	Annual		Quarterly	
	ρ	α	ρ	α
Canada (Budget)	0.86	0.70	0.95	0.23
	(0.016)	*(0.039)*	*(0.011)*	*(0.010)*
UK (Budget)	0.84	0.66	0.94	0.16
	(0.017)	*(0.024)*	*(0.012)*	*(0.007)*
US (Budget)	0.85	0.89	0.94	0.72
	(0.018)	*(.045)*	*(0.012)*	*(0.032)*
US (SPF)	0.97	0.84	0.99	0.52
	(0.009)	*(0.036)*	*(0.007)*	*(0.055)*

Table 2.1: Estimated values of α and ρ at annual and quarterly frequencies.

Note: Bootstrapped standard errors based on 1000 replications of the residuals are reported in parentheses.

broad item includes all government outlays net of servicing or repayment of debt.[15] We complement such series with their one-year-ahead forecasts, as reported by the government in its budget.

We divide both series by population and by the GDP implicit price deflator and then detrend them with a linear trend. The population series was first disaggregated at a quarterly frequency using standard disaggregation techniques[16] and then aggregated at a FY frequency. The resulting series of actual expenditures along with the one-year-ahead forecasts are reported in Figure 2.11 in 2.8.

The estimated process is fairly persistent ($\rho = 0.86$), while the share of news in the signal is approximately 70%. When translated into quarterly frequency, we obtain $\rho = 0.95$ and $\alpha = .23$. The dynamics of news and noise are reported in Figure 2.1. A reduction in news and noise volatility is observed during the 90s in conjunction with the start of the so-called "Great Moderation", while no significant increase in volatility is recorded at the time of the global financial crisis. Such a result is consistent with the narrative that Canada was among the few developed countries not significantly impacted by the global financial crisis. Thus, no specific fiscal actions (i.e., neither stimulus nor austerity measures) were implemented by policymakers due to the

[15]It would have been desirable to analyze more narrow series for government consumption and investment, but the lack of available data led us to use the above-described series.

[16]We use the "tempdisagg" package in R using the Denton-Cholette disaggregation method.

crisis.

Canada

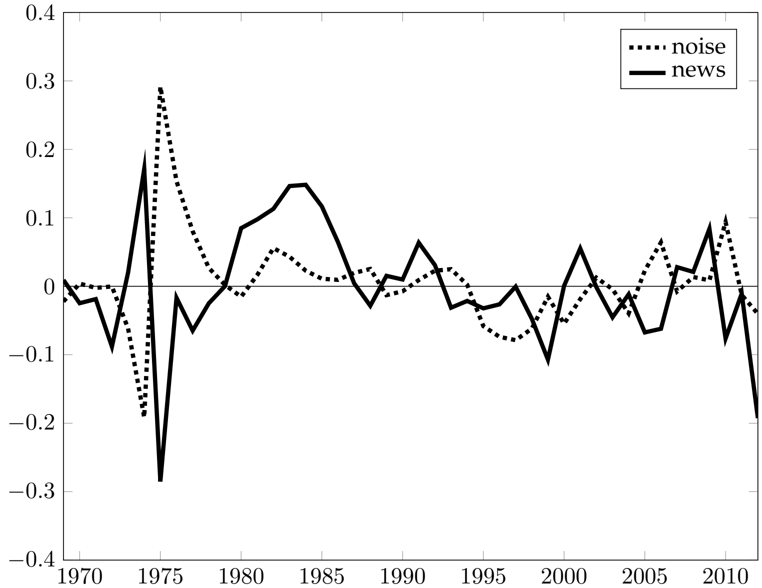

Figure 2.1: Dynamics of news and noise in Canada

Note: This figure plots the estimated dynamics of news and noise in the Canadian data.

United Kingdom

To identify the contribution of news and noise in government spending for the UK, we use the historical official forecasts database made available by the Office for Budget Responsibility.[17] This database collects the forecasts made for each year's budget as presented by the government, which usually occurs in March for the following FY.[18] We focus on forecasts for total managed expenditures (TME), which is a broad measure of total government spending in the UK that includes public sector current expenditures, public sector net investment and depreciation, transfers and debt servicing. The forecasts are available for FY 1989-90 to FY 2012-13.

We also collect data on actual TME. This series is available at annual frequency from FY 1946-47 to FY 2012-13.

[17]See http://budgetresponsibility.org.uk/data.

[18]In the UK, the FY starts in April and ends in March of the next calendar year.

We first divide this series by a price index to obtain the variables expressed in real terms.[19] Then, we detrend them by a linear trend and compute the autoregressive parameter and the variance. The estimated autoregressive parameter is 0.84, a value that is very similar (0.94), when converted to quarterly frequency, to the value obtained for Canada. The value of α at an annual frequency is estimated to be 0.66, thus implying a higher share of noise in the signal than in the Canadian data. This implies an even smaller value for α at a quarterly frequency (0.16). It should be stressed, however, that such a value may also be affected by the short series available (23 years). This limitation notwithstanding, a reduction in news and noise can be observed from 2000 to 2009 (see Figure 2.2), while an increase in volatility can be observed more recently, possibly related to the adoption of tighter fiscal policy by the UK government.

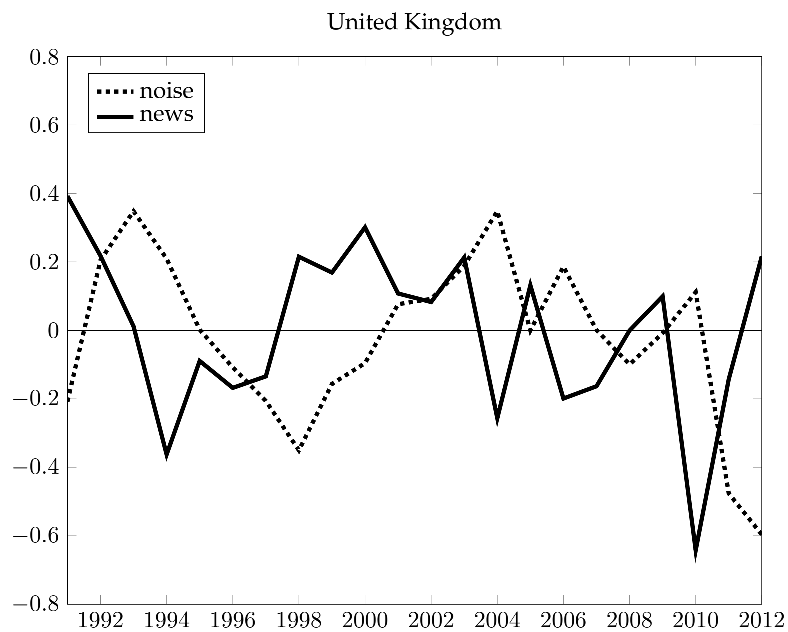

Figure 2.2: Dynamics of news and noise in the United Kingdom

Note: This figure plots the estimated dynamics of news and noise in the UK data.

[19] We make use of the GDP deflator from 1955 to 2012, while from 1946 to 1954, we make use of the long-term indicator of consumer goods and services prices (source: ONS).

United States

To estimate news and noise in US government spending, we use two distinct datasets. Our main reference will be the annual federal budgets, but we also use SPF data, which allows to perform some robustness checks.

Budget data

We first gather data on actual and forecasted "Total Budget Outlays" extracted from the US federal budgets from 1968 to 2013. The series displays a degree of persistence broadly in line with that observed for Canada and the UK ($\rho = 0.85$ at an annual frequency, $\rho = .94$ at a quarterly frequency). However, the share of news in the signal the agents receive is higher than in the previous cases, approximately 0.89 at an annual frequency, which implies $\alpha = 0.72$ at a quarterly frequency. As can be observed in Figure 2.3, the volatility of news and noise sharply has increased in recent years, especially in 2009 (possibly due to the enactment of the American Recovery and Reinvestment Act), 2010 and 2012.

Survey of Professional Forecasters

We complement the above findings using an alternative source of quarterly government spending data, the SPF. The item we focus on is the median forecast of real federal government consumption expenditures and gross investment (the variable RFEDGOV). The information structure of the SPF is as follows. Forecasters are provided with information about the realization in the preceding quarter; hence, they know g_{t-1}. They receive a questionnaire at the end of the first month of quarter t, which they submit by the middle of the second month of period t. It is fair to assume that they have noisy information about g_t, whose preliminary estimate will only be available in the future, that is, at the end of t. Therefore, we consider forecasts of g_t that are made in period t to be noisy. In this way, we access forecasts up to five periods ahead.

As the government spending series in the SPF has been subject to several revisions, we rebase the series on the NIPA federal government current receipts and expenditures series divided by the CPI. Both the actual series and the forecasts are then detrended by a linear trend. Table 2.1 reports the results of the estimation procedure. The autoregressive parameter is very persistent and close to 1 (it is .987). The variances of the news and noise shocks are very close, thus implying that $\alpha = 0.52$. Compared to the estimates obtained from budget data, the degree of persistence is higher, while the share of news in

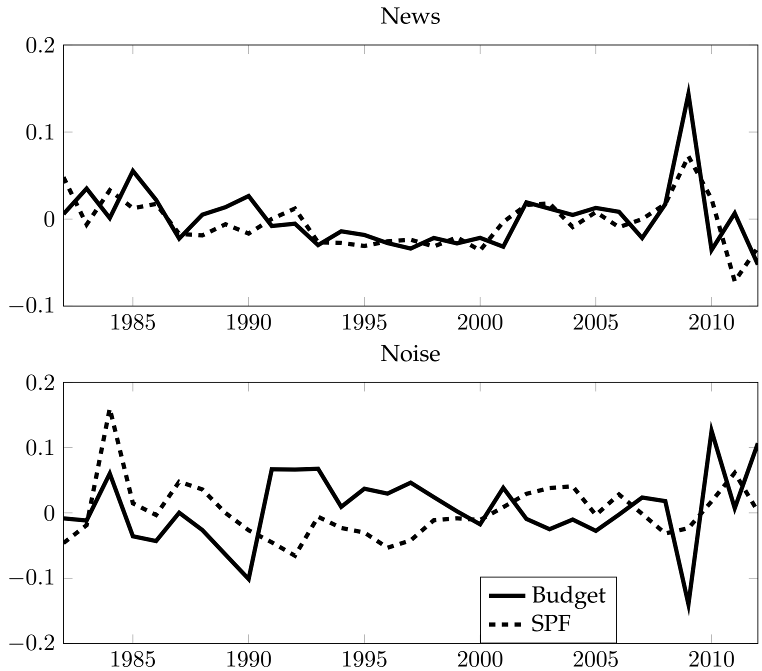

Figure 2.3: Dynamics of news and noise in the US

Note: This figure plots the estimated dynamics of news and noise in US budget data and annualized SPF data.

the signal is lower. This suggests that agents in the economy perceive fiscal policy as being more noisy than it really is. Overall, the SPF data confirm the robustness of our findings. In Figure 2.3, we plot the annualized series of news and noise shocks as identified using the budget data and the SPF data. The news series is very similar across these two datasets. For the noise series, notice that they qualitatively capture the same dynamics, especially during the 80s. Such a result seems to confirm the robustness of the estimation exercise, taking into account that the datasets are related to different time series, computed at different frequencies and over time spans that only partially overlap.

On the rational expectations hypothesis As an aside, it is worth noting that implicit in our methodology is an assumption of rational expectations.

In other words, we assume that forecasts are unbiased and efficient.[20] To support this assumption, we checked our dataset to determine whether the forecast errors ($E_{t-1}g_t - g_t$) indeed have a zero mean and whether their distribution is not skewed or normal. If forecast errors have zero mean, then the forecasts are, on average, unbiased. The results of these tests are reported in Table 2.3 in 2.10. The hypothesis of a zero mean for the forecast errors is confirmed across all countries at a 95 percent confidence interval. The skewness of distribution of the forecast errors is examined using the D'Agostino skewness test, whose null hypothesis implies that the data are not skewed. The results of the test confirm that the UK and US data do not display a significant degree of skewness, whereas the null hypothesis for Canada is rejected.[21] The normality test performed via the Jarque-Bera test, indicates that the forecast errors computed on UK and US budget data are normally distributed, while the errors for Canadian budget data and US SPF data are not. Overall, these findings suggest that the distribution of forecast errors is centered at zero and not skewed. Therefore, at a minimum, they imply that the rational expectations hypothesis cannot be discarded.

Robustness checks using SPF data

The quarterly frequency of the SPF data allows us to perform further robustness checks on the possible endogeneity of noise. Indeed, one may claim that what we have labeled "noise" so far could be mere model misspecification that arises from ignoring the endogenous response of fiscal policy to macro variables. Therefore, we assume that the government spending rule is of the kind

$$g_t = \rho g_{t-1} + \gamma X_t + \varepsilon_{t-q}, \tag{2.5}$$

[20]We are aware of potential issues related to bias in both forecasts and data revisions, but we decided to rely on the assumption of rational expectations for two reasons. First, we deem the costs of departing from this hypothesis (in terms of both the number of degrees of freedom for the underlying assumptions and the complexity of the empirical approach) to outweigh the benefits. Second, as discussed next in the text, our dataset seems to satisfy, overall, the rational expectations hypothesis, which is in line with the findings of Pesaran and Weale (2006).

[21]More precisely, the forecast errors for Canada display negative skewness, thus indicating that realizations of government spending tend to outperform forecasts – although, on average, the forecast error is zero. However, a close inspection of the Canadian time series reveals that the skewness is due to two data points (related to the years 1974 and 1975). If one removes these two points from the series, the null hypothesis for skewness is confirmed.

where X_t is a measure of economic activity such as real per capita GDP (in log-deviation from a linear trend) or the level of detrended TFP.[22]. Alternatively, X_t may be a dummy for NBER recession dates or for the political party in power during period t. The former aims to control for structural differences in the path of government spending during recessions, while the latter aims to control for different political spending styles. To estimate news and noise in such a model, we need to observe $\hat{E}_t X_{t+1}$. To maintain tractability, we use the realization of X_{t+1} (thus assuming perfect foresight of this variable).

We then estimate both OLS regressions and IV regressions (using the one-period lag of X_t as the instrumental variable) for equation (2.5) and report the results in Table 2.2. In all these cases, we obtain a level of noise that is similar to the process without an endogenous component. These findings thus confirm that the source of noise in the data is outside the model.

Endogenous component	GDP		TFP		NBER recessions	Democrat Republican
	OLS	IV	OLS	IV	OLS	OLS
ρ	0.9862	0.9858	0.9856	0.9856	0.9859	0.9860
	(0.0095)	*0.0095)*	*(0.0108)*	*(0.0108)*	*(0.0095)*	*(0.0095)*
γ	0.1084	-0.0569	0.0004	0.0004	-0.0039	0.0008
	(0.0748)	*(0.0831)*	*(0.000)*	*(0.0002)*	*(0.0035)*	*(0.0056)*
α	0.52	0.54	0.56	0.56	0.51	0.53
	(0.0463)	*(0.0563)*	*(0.0582)*	*(0.0567)*	*(0.0505)*	*(0.0543)*

Table 2.2: Estimates of α with endogenous components in the spending rule.

Note: In the IV regressions, we use lagged realizations of X_t as instruments. Standard errors are reported in parentheses. Standard errors for the α parameter are obtained through a bootstrapping procedure based on 1000 replications of the residuals.

To check the goodness of fit of our approach, we also simulated data (see Table 2.4 in 2.10). More precisely, we modified our DSGE model by introducing an endogenous government spending rule as in (2.5) with the log of detrended GDP on the right-hand side. The parameters were calibrated on the IV regression with GDP.[23] We then generated simulated data for 1000 periods from the model assuming that news and noise shocks were the only sources

[22]The source for this GDP data is the US Bureau of Economic Analysis, while for TFP, the source is the Federal Reserve of San Francisco (see http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/)

[23]Therefore, the parameters were set as follows: $\rho = 0.9858$, $\gamma = -0.0569$ and $\alpha = 0.54$.

of economic fluctuation and estimated the regressions using these simulated data to determine whether the true parameters could be recovered. The results reported in Table 2.4 show that the values of the parameters estimated via an IV approach are close to the values of the true parameters. Interestingly, given that the feedback coefficient is found to be non-significant in the IV regression, a simple AR(1) estimation would be able to generate values for ρ and α that are very close to the true values.

2.5 Quantitative results from the DSGE model

The model is log-linearized around the non-stochastic steady state and solved using standard methods. The values of the parameters, which are reported in 2.9, are taken from Mertens and Ravn (2011) and Chahrour, Schmitt-Grohé, and Uribe (2012), with the notable exception of the parameters related to government spending and information flows. Although the parameters in the original Mertens and Ravn (2011) paper were estimated using US data, we apply the same calibration to the UK and Canada to compare their output with that of the US model. Furthermore, to make the results comparable across countries, and because the augmented Dickey-Fuller and Phillips-Perron tests do not reject the unit root hypothesis, we conduct simulations for these countries setting the autoregressive parameter of government spending equal to 1. Note, however, than none of our qualitative results is due to the fact that we assume that $\rho = 1$ in the government spending process. The quantitative results do not change significantly as long as the government spending process displays enough persistence.[24] Lastly, for comparability we set $q = 4$ for all countries, a fairly conservative value in line with the literature on fiscal news (Born et al. 2013,Leeper et al. 2013, Mertens and Ravn 2011 and Schmitt-Grohé and Uribe 2012).

Inspecting the mechanism

Before comparing the outcomes of the model under the estimated values of α, Figure 2.4 plots the IRFs for output, non-durables, durable goods and investment reactions to a news and a noise shock in a fictitious case wherein the amount of noise is equivalent to the amount of news (i.e., $\alpha = .5$). Note that output jumps up in period 4 only if the announced increase in government spending actually takes place; if the announcement turns out to be pure

[24]For a discussion of the macroeconomic role of government spending persistence, see Dupaigne and Fève (2015).

noise it means that no actual spending occurs. As expected, the shapes of the IRFs are the same for noise and news until the shock actually occurs. This similarity is due to the fact that agents in this economy are not able to identify the source of the variation in the signal. An important corollary is that choice variables also react to a noise shock until the news event is realized. Moreover, noise shocks affect real variables even after their non-fundamental nature is revealed. In other words, when an announcement is at least partially noisy (i.e., $\alpha > 0$), an announced increase in government spending is able to generate a positive response of output even if the positive signal is due entirely to noise.

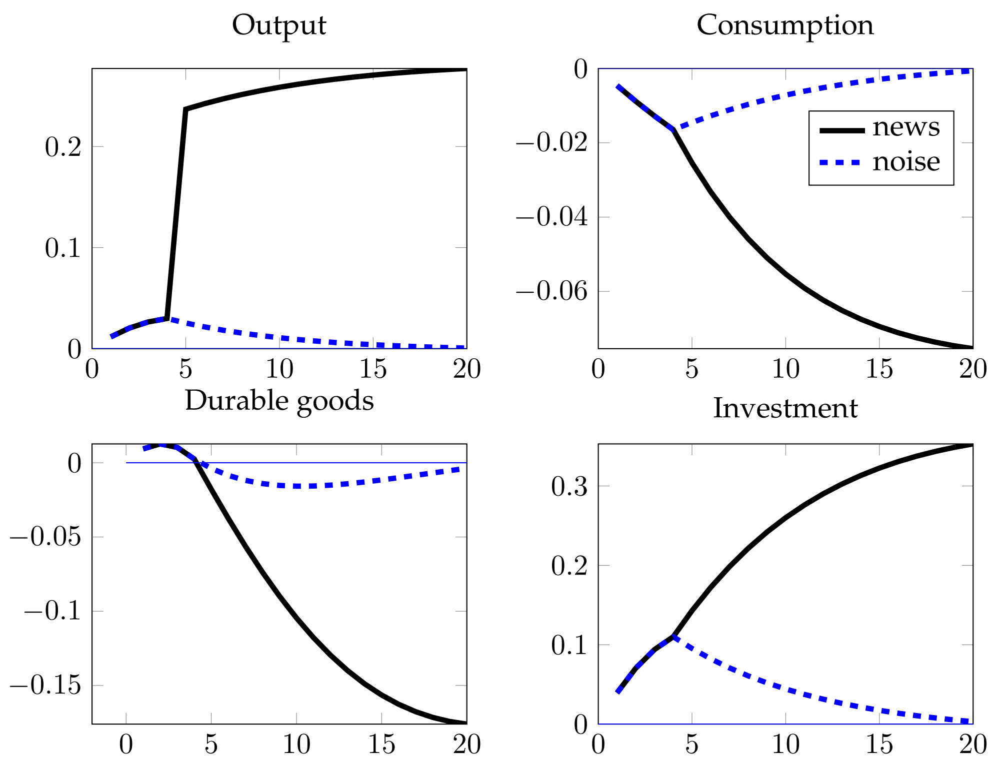

Figure 2.4: IRFs for output, consumption, durable goods and investment to a noise and a news shock

Note: This figure plots the IRFs for output, non-durables consumption, durable goods consumption and investment (as percentages) to a 1 percent shock to government spending under a mild level of noise ($\alpha = 0.5$).

The long-lasting effect of noise can be gauged by performing a variance decomposition of news and noise shocks at different horizons for the above variables. These results are plotted in Figure 2.5. Noise still explains approximately 20 percent of the investment variance after 10 periods while the percentage is a bit lower for consumption of both non-durable and durable goods. The variance of output is much less affected by noise after that noise is revealed. This pattern is due to the fact that output is the sum of consumption, durables, investment and government spending, and this latter variable (which exhibits no variance before period 5) is not affected by noise.

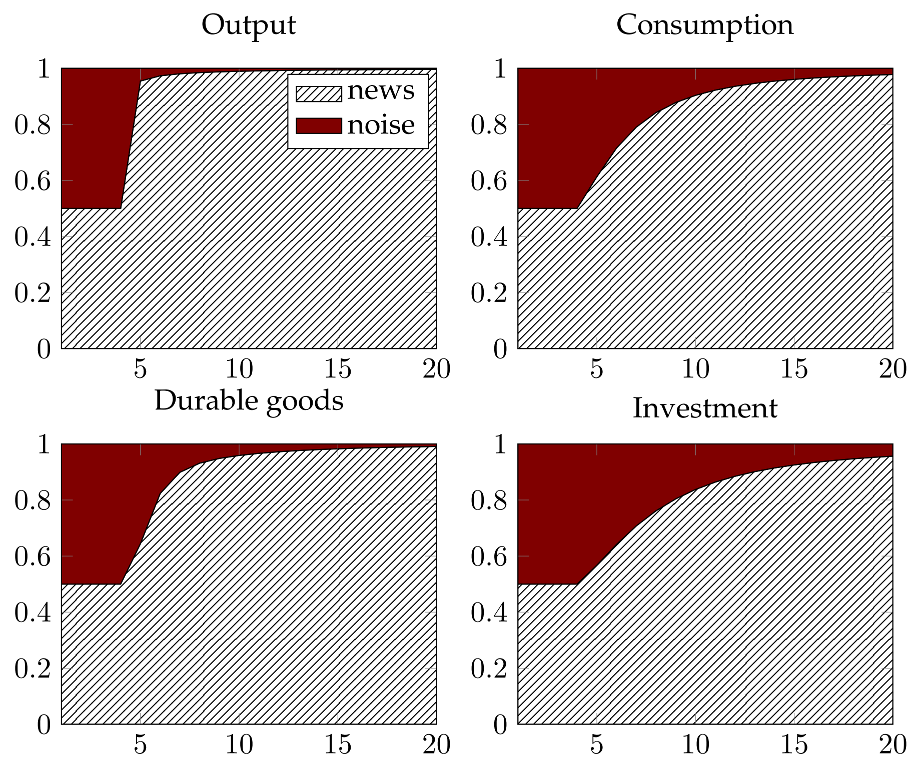

Figure 2.5: Conditional variance decomposition of news and noise shocks at different horizons

Note: This figure plots the conditional variance decomposition of news and noise shocks at different horizons for output, consumption of non-durables, consumption of durable goods and investment under a mild level of noise ($\alpha = 0.5$).

Quantifying the effect of noisy news

We investigate the quantitative impact of noise by comparing the IRFs for a news shock under different assumptions about the information flow. More precisely, we compare the outcome of an economy under perfect information about government spending ($\alpha = 1$) to one under the parametrization implied by the estimated noise to signal ratio in Table 2.1. For the value of α in the US, we rely on budget data for consistency with the UK and Canada datasets, which are also based on budget data. The results of this exercise are reported in Figure 2.6.

Note that the main role played by noise is to mitigate the dynamics of the variables. Additionally, due to real rigidities, even after the shock is realized, agents' reactions tend to lag behind the reaction observed under perfect information. Comparing the outcomes under partial information, the response of the UK and Canada are similar, while as expected, the reaction of the US is closer to the full information benchmark.

In Figure 2.6, the variable that reacts the most is investment. This result is much in line with the view of news shocks as an inducer of "animal spirits" (see Beaudry and Portier 2014) and is related to the fact that investment is a forward-looking variable mainly because it cannot immediately adjust to external shocks. However, the presence of noise dampens the adjustment of investment. As for consumption and durable goods, investment under-reacts until the uncertainty is resolved (in period 5), and then, a phase of gradual catch-up to the perfect information case occurs.

We now address the issue of quantifying the impact of noise on some measures of fiscal multipliers. First, note that over the long run, the economy is not affected by imperfect information: the long-run multiplier for output, defined as the relative variation in the steady states of output and government spending after a persistent government spending shock, is equal to 1.35, irrespective of the severity of the information issue because when the news shock is realized, agents will be able to infer it from the dynamics of government spending and will thus gradually adjust their choices. Over the short to medium run, however, the picture can substantially change due to the frictions generated by imperfect information.

To quantify the impact of information frictions on the transmission of fiscal policy shocks, we compute two measures of the government spending multipliers for output, consumption and investment.[25] The first one is com-

[25]Multipliers for durable goods are reported in 2.8.

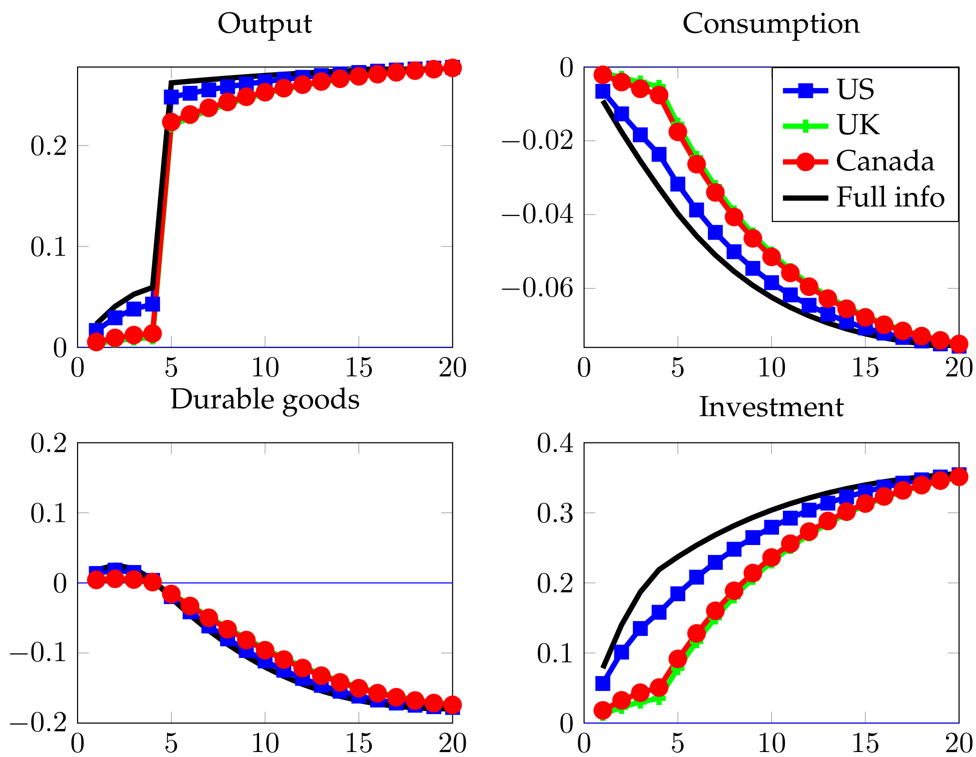

Figure 2.6: IRFs for a news shock

Note: This figure plots the IRFs for output, non-durable consumption, durable goods consumption and investment (as percentages) reactions to a 1 percent shock in government spending under the assumption of perfect information ($\alpha = 1$) vs the estimated level of noise for Canada, the UK and the US.

puted as

$$GSM_t = \frac{\widehat{X}_t}{\widehat{g}_q}\frac{X}{G}$$

for $t = 1, ..., T$, where X_t is alternatively output, consumption or investment, while X and G denote the steady state values, and variables with a hat are log-deviations from the steady state.

The second measure is the net present value of the multiplier (Mountford and Uhlig, 2009), which is computed according to the formula

$$NPV_t = \frac{\sum_{j=0}^{k} \beta^j \widehat{X}_{t+j}}{\sum_{j=0}^{k} \beta^j \widehat{g}_{t+j+q}}\frac{X}{G}.$$

Note that in the first case, the denominator is lagged forward as the news shock occurs in period $t + q$. In the upper panels of Figure 2.7, the values of GSM_t and NPV_t for output are reported for the three economies considered along with the full information benchmark.

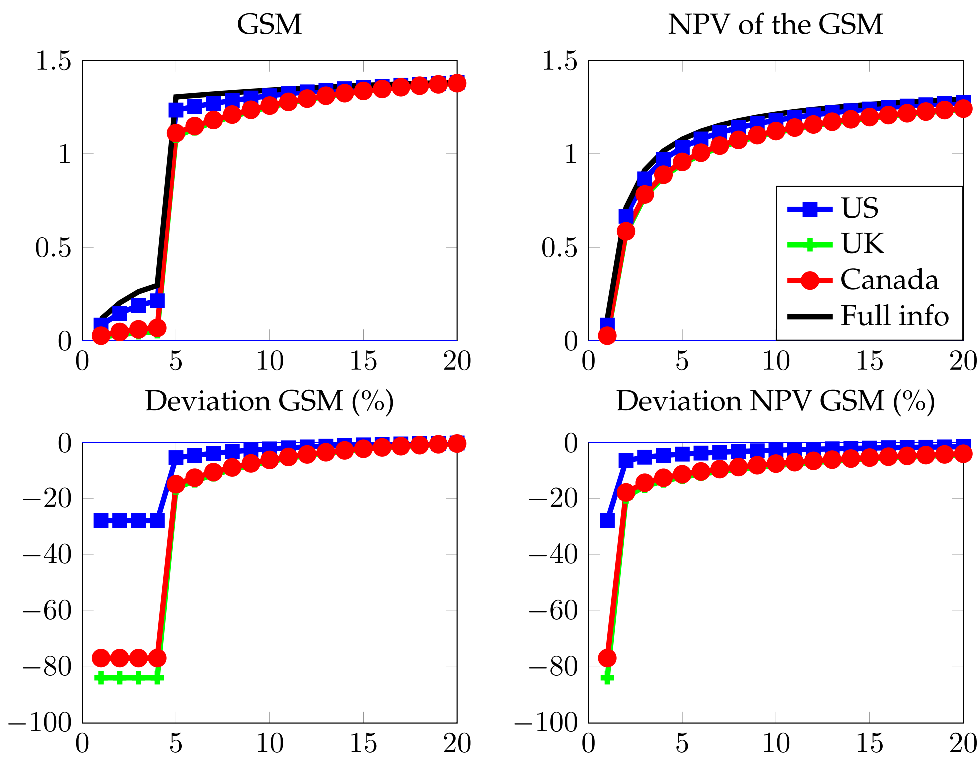

Figure 2.7: Output multipliers and deviation from the full information multipliers

Note: This figure plots the multipliers for output and the deviation (as a percentage) under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$, where X is alternatively the GSM and the NPV of the GSM, and $i = CA, UK, US$.

In both cases, the values of the multipliers under partial information are consistently lower than in the case of perfect information. To gain a quantitative insight into the loss for each economy due to information frictions, we compute the distance in percentage terms of the multiplier for each economy from the corresponding full information multiplier. The results are reported in the lower panels of the figure and expressed in percentage terms. Note that if one considers the GSM, the losses for the UK and Canada are well above 80% until the news is realized. In fact, the loss from the full information multiplier is exactly equal to $1 - \alpha$ and is not dependent on the value of the parameters or on the frictions in the model.[26] After the realization of the news shock, the loss falls to approximately 15 percent or less, while the multiplier gradually converges to its long-run value. The loss for the US is less severe on impact (28 percent), but still notable.

If we consider the multipliers for consumption and investment (Figure 2.8), we note that the negative effect on consumption is fairly small (up to -0.15 over the long run). The effect on investment, however, is significant. The potential of investment is dampened by noise: the investment multiplier soon after the shock is realized (period 5) is approximately 0.4 under full information. This value drops significantly to 0.2 or less in all three cases when imperfect information is considered. In contrast to the multiplier on output, such a multiplier loss is not rapidly recovered after the realization of the shock. For example, in period 10, both consumption and investment multipliers in noisy environments are still approximately 20 percent less than the level one would have observed under full information.

2.6 Conclusion

The role of imperfect information in business cycles is one of the most promising research paths recently explored in macroeconomics. In this paper, we highlighted the relationship between imperfect or "noisy" information and the conduct of fiscal policy.

Using official forecasts of government spending as reported in the annual budgets of Canada, the UK and the US, we demonstrated the implementation of a limited information approach (a simple method of moments) to identify news and noise. The amount of noise observed for these three countries is significant: on average, the percentage of noise in official government spending forecasts ranges from 28% to 84%. Using these values in a richer DSGE setting, we highlighted the detrimental effects on fiscal multipliers, particularly on investment multipliers.

[26]We also performed the above exercises using alternative specifications of the model (results available upon request). More precisely, we removed durable goods and introduced nominal frictions in the form of Calvo pricing to a model *à la* Smets and Wouters. All of the above results hold, and for a reasonable calibration of the parameters related to price stickiness and monetary policy reaction, we quantitatively obtain very similar values for multipliers from period 5 on.

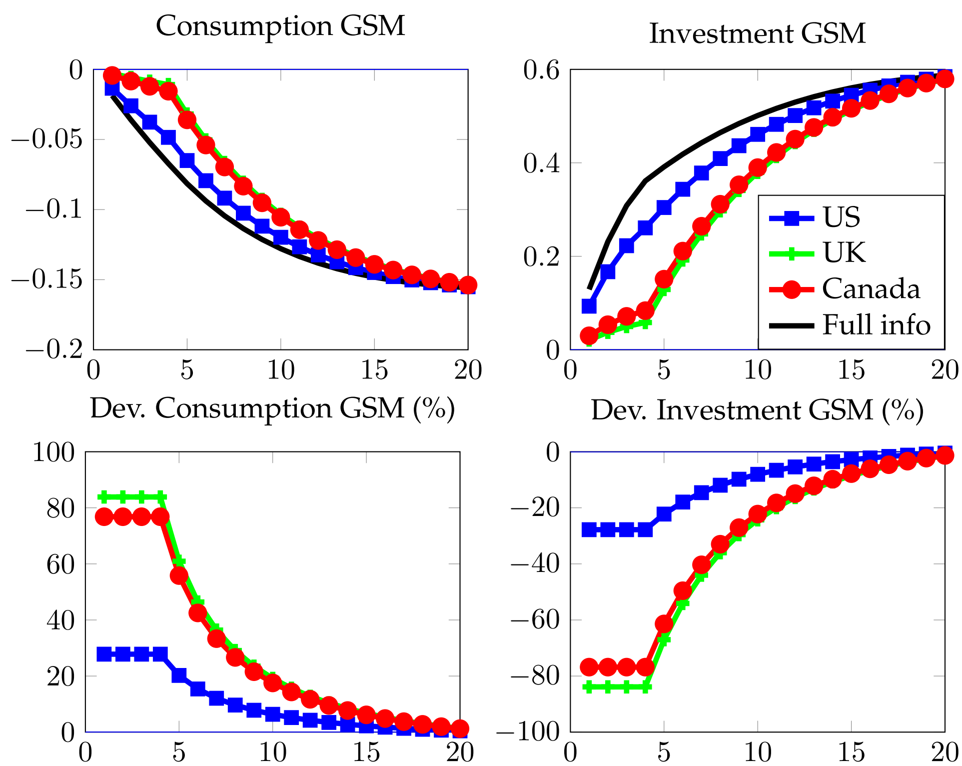

Figure 2.8: Consumption and investment multipliers and deviation from full information multipliers

Note: This figure plots the multipliers for consumption and investment and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

Our approach can be fruitfully extended to other policy settings in which announcements play crucial roles, such as monetary policy (forward guidance) or banking regulations and structural reforms implemented with lags.

2.7 Appendix: Further results on misspecification

Estimation of $\widetilde{\alpha}$

The true data generating process (DGP) is an AR(2) process

$$\hat{g}_t = \rho_1 \hat{g}_{t-1} + \rho_2 \hat{g}_{t-2} + \varepsilon_{t-1}$$

and the misspecified AR(1) model is written

$$\hat{g}_t = \rho \hat{g}_{t-1} + \tilde{\varepsilon}_{t-1}$$

Under the AR(2), we first estimate the parameter ρ in the AR(1) model. From the first order autocorrelation of an AR(2) process (see Hamilton 1994b), we deduce

$$\rho = \frac{\rho_1}{1-\rho_2}$$

To obtain an estimate of α in the misspecified AR(1) model, we linearly project $E_t \hat{g}_{t+1} - \rho \hat{g}_t$ on $\hat{g}_{t+1} - \rho \hat{g}_t$. We deduce

$$\begin{aligned}
\tilde{\alpha} &= \frac{Cov\left(E_t \hat{g}_{t+1} - \rho \hat{g}_t, \hat{g}_{t+1} - \rho \hat{g}_t\right)}{V\left(\hat{g}_{t+1} - \rho \hat{g}_t\right)} \\
&= \frac{Cov\left((\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \alpha(\varepsilon_t + \nu_t), (\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \varepsilon_t\right)}{V\left((\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \varepsilon_t\right)} \\
&= \frac{((\rho_1 - \rho)^2 + \rho_2^2) V(\hat{g}_t) + 2(\rho_1 - \rho)\rho_2 Cov(\hat{g}_t, \hat{g}_{t-1}) + \alpha \sigma_\varepsilon^2}{V\left((\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \varepsilon_t\right)} \\
&= \frac{\left(\frac{\rho_1^2 \rho_2^2}{(1-\rho_2)^2} + \rho_2^2\right) V(\hat{g}_t) - 2\frac{\rho_1 \rho_2^2}{1-\rho_2} Cov(\hat{g}_t, \hat{g}_{t-1}) + \alpha \sigma_\varepsilon^2}{V\left((\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \varepsilon_t\right)}
\end{aligned}$$

Using the autocovariances (at orders 0 and 1), we deduce

$$\begin{aligned}
V(\hat{g}_t) &= \frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2 - \rho_1^2)} \\
Cov(\hat{g}_t, \hat{g}_{t-1}) &= \frac{\rho_1}{1-\rho_2} \frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2 - \rho_1^2)} \\
V\left((\rho_1 - \rho)\hat{g}_t + \rho_2 \hat{g}_{t-1} + \varepsilon_t\right) &= \frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)\left((1-\rho_2)^2 - \frac{\rho_1^2 \rho_2^2}{(1-\rho_2)^2}\right)}
\end{aligned}$$

After replacement into $\tilde{\alpha}$, we deduce

$$\begin{aligned}
\tilde{\alpha} &= \frac{\left(\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}+\rho_2^2\right)\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}-2\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}+\alpha\sigma_\varepsilon^2}{\frac{(1-\rho_2)\sigma_\varepsilon^2}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\left(\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}+\rho_2^2\right)\frac{(1-\rho_2)}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}-2\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\frac{(1-\rho_2)}{(1+\rho_2)((1-\rho_2)^2-\rho_1^2)}+\alpha}{\frac{(1-\rho_2)}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\frac{\rho_2^2}{1-\rho_2^2}+\alpha}{\frac{(1-\rho_2)}{(1+\rho_2)\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)}} \\
&= \frac{\rho_2^2}{1-\rho_2^2}\frac{1+\rho_2}{1-\rho_2}\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)+\frac{1+\rho_2}{1-\rho_2}\left((1-\rho_2)^2-\frac{\rho_1^2\rho_2^2}{(1-\rho_2)^2}\right)\alpha \\
&= \left(\frac{\rho_2^2}{1-\rho_2^2}\right)\left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho 1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho 1-\rho_2}{1-\rho_2}\right)\right) \\
&\quad +\left(\frac{1+\rho_2}{1-\rho_2}\right)\left(1-\rho_2\left(\frac{1-\rho 1-\rho_2}{1-\rho_2}\right)\right)\left(1-\rho_2\left(\frac{1+\rho 1-\rho_2}{1-\rho_2}\right)\right)\alpha
\end{aligned}$$

A simple illustration of misspecification

Let us assume that the true data generating process (DGP) is an AR(1), but we wrongly assume that government spending does not display serial correlation. To obtain an estimate of α in the misspecified AR(1) model, we linearly project $E_t\hat{g}_{t+1}$ on $\hat{g}_{t+1}$ and use the true stochastic process of government spending. The estimated value for α in the misspecified model under the true DGP is given by

$$\widetilde{\alpha} = \rho + \alpha(1-\rho^2)$$

Assume that $\rho \in [0,1]$, i.e., government spending can display serial correlation. This implies that $\widetilde{\alpha} \geq \alpha$, so we will underestimate the size of the noise. For example, if $\rho \to 1$, the estimated value tends to one. Thus, we will incorrectly conclude that there is no noise in government spending policy.

2.8 Appendix: Additional graphs

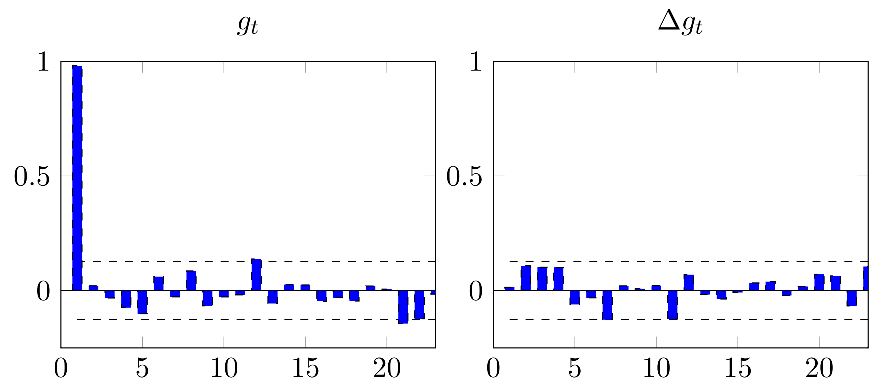

Figure 2.9: Partial autocorrelation of government spending in the US

Note: In this figure, the autocorrelation functions for the quarterly log-series of real per capita government spending in the US (linearly detrended from 1952Q1 to 2014Q1, left panel) and for its first difference (Δg_t, right panel) are plotted. Confidence intervals are at 95% level. Series: "Real Government Consumption Expenditures and Gross Investment" (id: GCEC96), source: U.S. Bureau of Economic Analysis; "Total Population: All Ages including Armed Forces Overseas", source: U.S. Department of Commerce, Census Bureau.

2.9 Appendix: Calibrated values

Parameter	Value	Description
γ_z	1.005	Trend
θ	.36	Capital share
Y	1	Steady state output
$\frac{G}{Y}$	0.201	Share of government spending
ν	1	Capital utilization at steady state
N	.25	Labor at steady state
$\frac{C}{D}$	7.4034	Consumption to durables
σ	3.7621	Elasticity of intertemporal substitution
b	0.8804	Habit formation
β	0.9742	Discount factor
κ	0.9759	Disutility of labor
ω_i	8.488	Adjustment cost for investment
ω_d	7.795	Adjustment cost for durables
ρ_g	1	Persistence of government spending shock
σ_g	.0548	Std dev of government spending shock

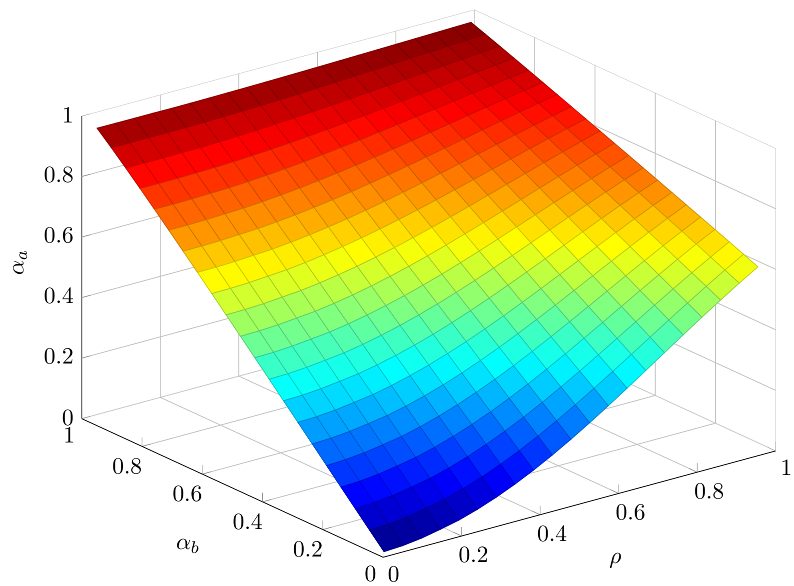

Figure 2.10: The binding function

Note: This figure plots the binding function that yields the share of news at a yearly frequency (α_a) as a function of the share of news and the autoregressive parameter of the quarterly series (α_b and ρ).

Note: The values of the parameters are taken from Mertens and Ravn (2011), except for the parameters related to the government spending process (ρ_g and σ_g).

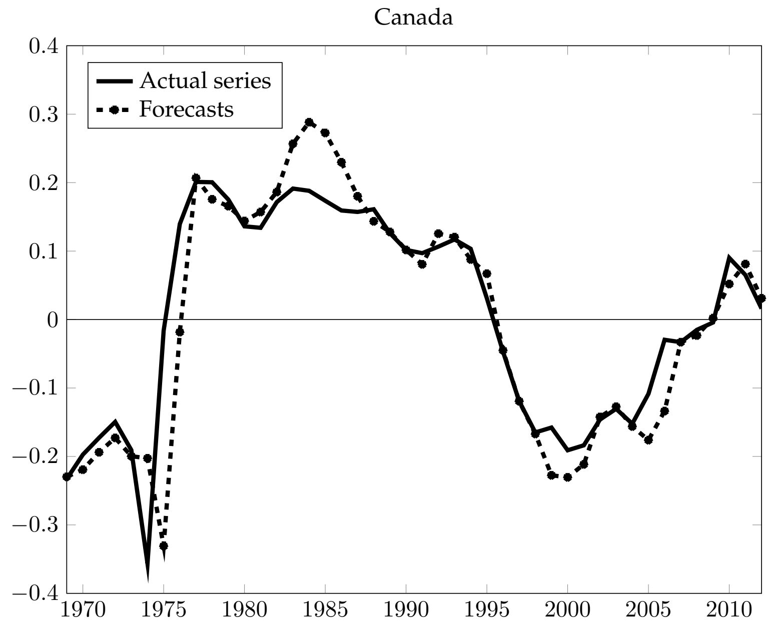

Figure 2.11: Log of detrended per capita real government spending in Canada

Note: This figure plots actual realizations and one-step-ahead forecasts of the log of detrended per capita real government spending in Canada.

2.10 Appendix: Additional tables

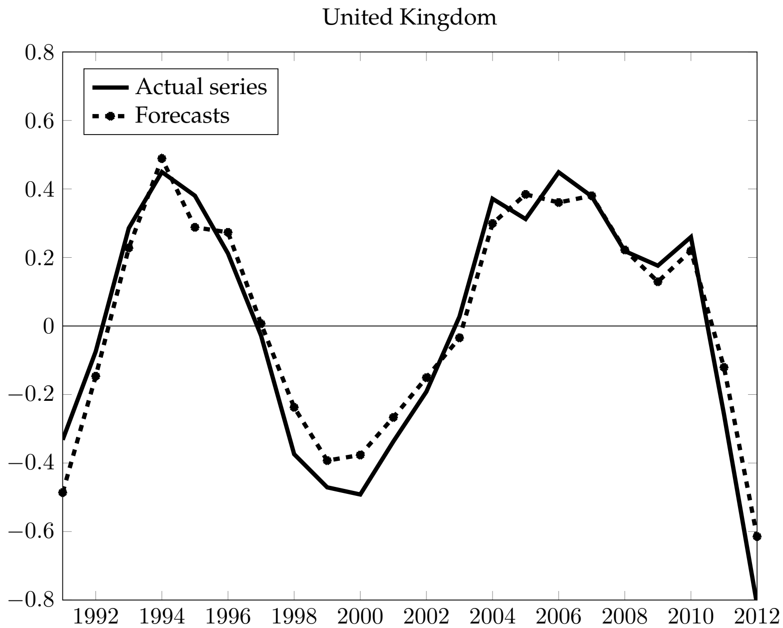

Figure 2.12: Log of detrended per capita real government spending in the UK

Note: This figure plots realizations and one step ahead forecasts of the log of detrended per capita real government spending in the United Kingdom.

2.11 Appendix: Durable goods multipliers and NPV GSM for consumption and investment

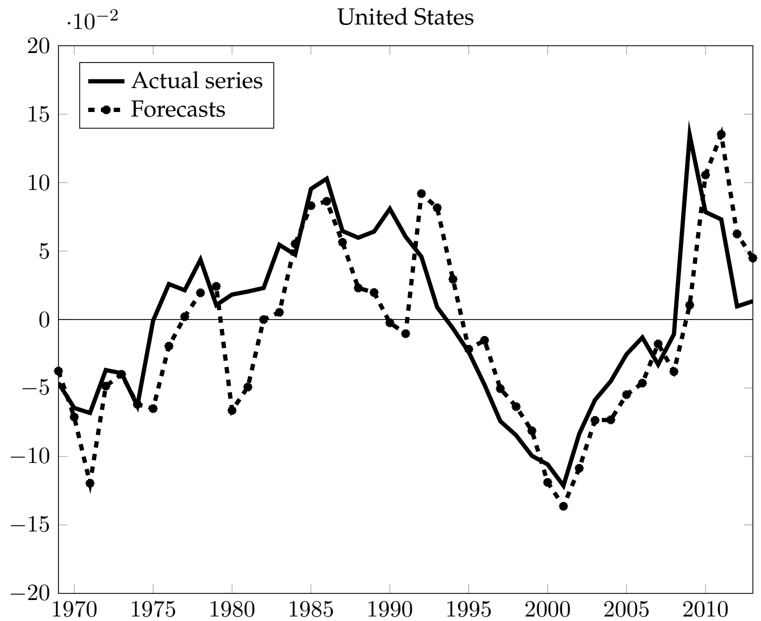

Figure 2.13: Log of detrended per capita real government spending in the US

Note: This figure plots realizations and one-step-ahead forecasts of the log of detrended per capita real government spending in the United States.

2.12 Appendix: Data sources

Canada

The following are the series for Canada:

- Government Spending: "Budget Expenditures" (up to 1982) and "Program Expenses" (from 1987). Source: Budget Speech and Budget Plan, various years.
- Population: "Total population". Source: World Bank (series id: SP.POP.TOTL)
- Price deflator: "GDP Implicit Price Deflator". Source: OECD.

United Kingdom

The following are the series for the UK:

Country	t-test ($\mu = 0$)	D'Agostino skewness test	Jarque-Bera test
Canada	-0.0073	Skew=-1.8754	χ^2_2= 144.6786
	[-0.0283; 0.0137]	*(0.0050)*	*(0.0000)*
UK	0.0014	Skew=0.1623	χ^2_2=0.6364
	[-0.0026; 0.0054]	*(0.804)*	*(0.7274)*
US (Budget)	-0.0125	Skew = -0.2756	χ^2_2=0.5967
	[-0.0248; -0.0002]	*(0.5802)*	*(0.7421)*
US (SPF)	-0.0016	Skew=-0.1480	χ^2_2=36.6799
	[-0.0043; 0.0011]	*(0.6335)*	*(0.0000)*

Table 2.3: Zero mean, skewness and normality tests on forecast errors.

In the t-test column, the lower and upper bounds of the 95 percent confidence intervals are reported in brackets. The D'Agostino skewness test and Jarque-Bera test p-values are reported in parentheses. The null hypothesis for the D'Agostino skewness test is that data have no skewness. The null hypothesis for the Jarque-Bera test is that data are normally distributed.

True parameters		AR(1)	IV
ρ	0.9858	0.9779	0.9786
		(0.0064)	*(0.0064)*
γ	-0.0569		-0.1047
			(0.1727)
α	0.54	0.55	0.55
		(0.0243)	*(0.0248)*

Table 2.4: Estimates of simulated data with endogenous components in the spending rule.

Note: In the IV regression we use the lagged realizations of GDP as the instrument. Standard errors are reported in parentheses. Standard errors for the α parameter are obtained through a bootstrapping procedure based on 1000 replications of the residuals.

- Government Spending: "Total managed expenditure". Source: UK Budget, various years.
- Population: "Mid-year population estimates". Source: ONS.
- Price deflator: "GDP Implicit Price Deflator". Source: OECD.

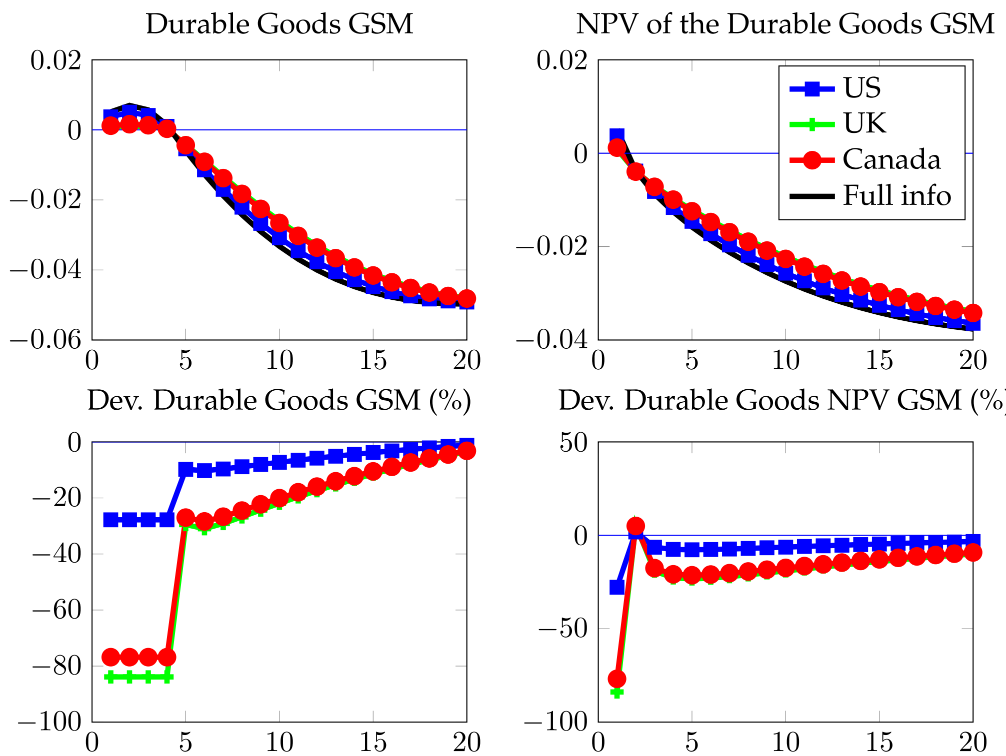

Figure 2.14: Durable goods multiplier and deviation from full information

Note: This figure plots the multipliers for durable goods and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

United States

The following are the series for the US:

- Government Spending (Budget): "Total budget outlays". Source: Federal Budget, various years.
- Government Spending (SPF): "Real Federal Government Consumption Expenditures and Gross Investment". Source: Survey of Professional Forecasters (series id: RFEDGOV).
- Population: "Total Population: All Ages including Armed Forces Overseas". Source: U.S. Department of Commerce: Census Bureau.

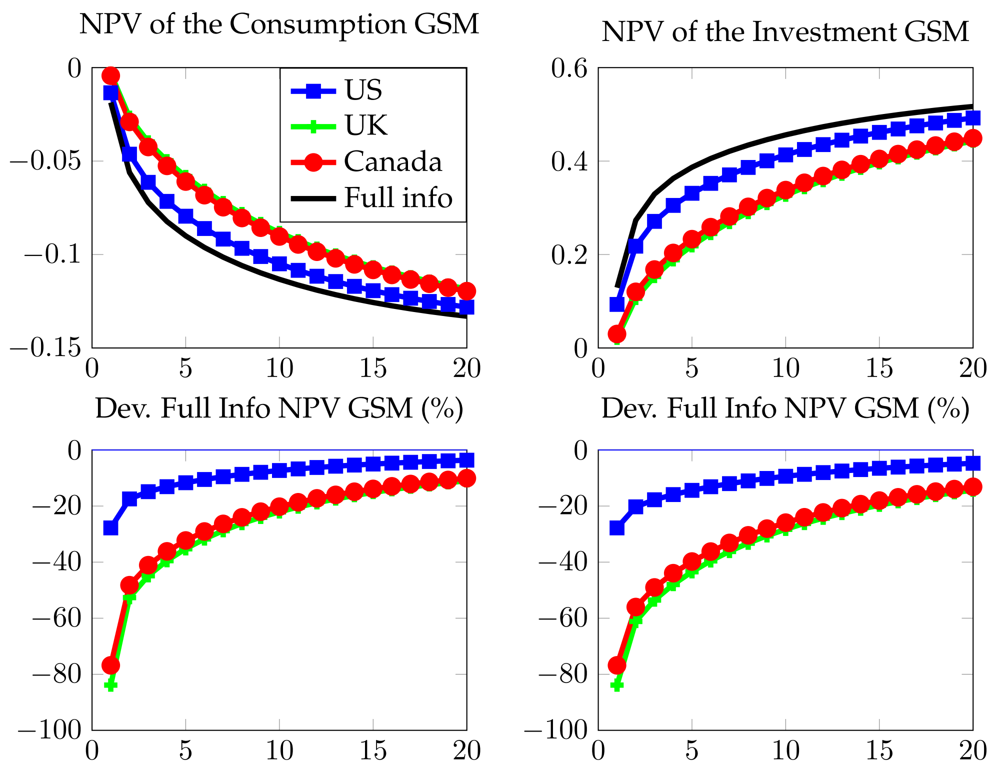

Figure 2.15: NPV multipliers of consumption and investment and deviation from full information

Note: This figure plots the NPV multipliers for consumption and investment and the deviation under partial information compared to the full information case. The figures in the bottom panel are computed as $\frac{X_t^i - X_t^{FI}}{X_t^{FI}}$ where X is alternatively the GSM and the NPV of the GSM and $i = CA, UK, US$.

- Price deflator: "Consumer Price Index for All Urban Consumers: All Items". Source: U.S. Department of Labor: Bureau of Labor Statistics.

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Chapter 3

Financial Frictions, Macroprudential Policies and the Real Economy

3.1 Introduction

After the Great Financial Crisis of 2008, the relevance of financial frictions in business cycle dynamics has been vastly investigated, with new strands of literature highlighting the role of the financial sector as a source of business cycle fluctuations and as a shock propagator (Brunnermeier et al., 2013). From a normative viewpoint, the role of financial frictions has spurred a debate on how to ensure stability in the financial system that has led to the development of a new set of so called "macroprudential" policy tools.[1] This label covers a variety of policies sharing the common objective of reducing systemic risk in the economy and of mitigating the financial cycle (Claessens, 2014). Some of these tools are already part of the standard toolkit of financial regulators.[2]

Their widespread adoption notwithstanding, surprisingly little quantitative research has been performed so far on the effects of such policies on the real economy. Most of the research on macroprudential policies is indeed theoretical and aimed at identifying the sources of systemic risk and at shaping

[1] It has to be acknowledged that economists working at the BIS first developed the concept of macroprudential policies in the late 1970s. See Clement (2010).

[2] As a way of example, at the end of 2015 in Europe the national measures in the EU/EEA notified to the European Systemic Risk Board (ESRB), or of which the ESRB was aware, of macroprudential interest were 213.

optimal policy intervention.[3] Thus, while it is well documented that macroprudential policies can help increase the soundness of the financial sector and thus also improve the performance of the economy as a whole, a quantitative assessment of the spillovers to the real economy is still lacking. Also, a major shortcoming of most quantitative models with a financial sector are usually solved performing a linear approximation around the steady state of the economy. This in turn implies that the impact of the financial sector on the economy is symmetric both in boom and in bust periods.

In this paper I attempt at quantitatively gauging the asymmetric impact on the real economy of financial frictions and at estimating the effectiveness of several macroprudential policies. I estimate the model on the Italian economy for two reasons. First, the financial frictions I want to investigate arise from within the banking sector and influence quantities and prices of bank loans to the economy. In this respect, the Italian financial system is an fitting example, as financial intermediation is mainly performed by traditional banks.[4] Secondly, in the last decade Italy experienced a double dip recession (see Figure 3.1) the first dip in 2009 was driven by the global turmoil after the Lehman crack.

The second was related to the European Sovereign debt crisis, whose effects on the real economy are still present. Such dynamics allow to investigate the ability of macroprudential policies to reduce the severity of crises arising from different exogenous shocks. The key research questions of the paper are then related to identify the impact on real variables of tensions arising in the banking sector and to investigate whether the timely implementation of macroprudential policies would have helped in mitigating the real effects of financial crises. In other words, I question whether there exist a one-size-fits-all macroprudential tool for dealing with financial crises.

I try and answer the above questions by making use of a DSGE model with a banking sector where financial frictions can bite only occasionally. This non-linearity within the banking sector should help in principle in identifying asymmetries in the cycle.[5] It will also help in investigating the behavior of macroprudential policies in a non-linear environment.

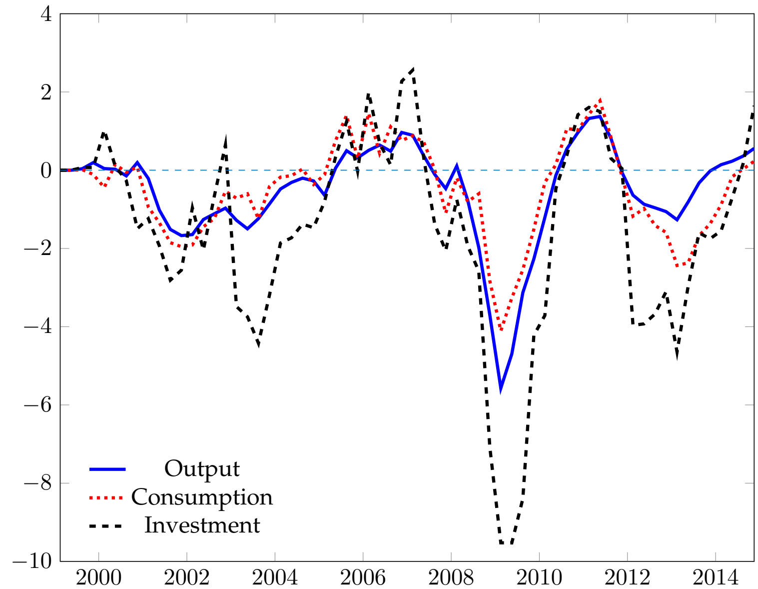
A further contribution of the paper is technical and is related to the esti-

[3] For a survey of the literature see for instance Galati and Moessner (2013).

[4] In 2013, banks accounted for almost 85 percent of total financial sector assets. The vast majority of Italian banks runs a traditional business model where the prevailing items on the asset side of the balance sheet are loans to the economy. The prevailing source of funding is deposits and customers loans (IMF, 2013).

[5] It has already been shown in the literature that occasionally binding financial constraints may give rise to asymmetric business cycles (Li and Dressler, 2011).

Figure 3.1: Business cycle dynamics for output, consumption and investment in Italy (1999-2014)



Note: This figure displays the dynamics of output, consumption and investment in Italy from 1999q1 to 2014q4. Series are detrended with a one-sided HP filter with smoothing parameter equal to 1600. Data are reported in per cent.

mation of large non-linear DSGE models. The model I am dealing with has indeed an occasionally binding constraint related to financial frictions in the economy; this implies that the model operates under two regimes: one in which financial frictions are in place and the other in which the allocation of resources is not affected by financial constraints. Such non-linearity is introduced to better capture the interaction between the financial system and the real economy. However, so far one of the main hurdles for investigating large non-linear models has been their computational complexity. Here I rely on a method recently brought forward in Guerrieri and Iacoviello (2015b) for solving this class of models. One of the advantages of this method lies in its computational simplicity, which makes it possible to bring a medium scale model to the data. I therefore introduce a new estimation technique for DSGE models that does not rely on the estimation of the likelihood function. This method, that is gaining popularity in other disciplines, is known as Approximate Bayesian Computation (ABC, see Beaumont et al. 2002). I show that ABC can be easily implemented for estimating non-linear DSGE models and it provides several advantages compared to other methods currently used in the estimation of non-linear DSGE models, such as the Simulated Method of Moments (Fernández-Villaverde and Rubio-Ramírez 2007, Ruge-Murcia 2012). I show that the non-linear model is better able than linear models to approximate the asymmetries that can be observed in the data. More precisely, the estimated model accurately replicates the negative skewness of output and it better matches higher order moments (such as skewness and kurtosis) of output, consumption and investment.

The current paper is related to two main strands of literature. First, it is related to papers that try and embed macroprudential policies in DSGE models with financial frictions (see for instance Kannan et al. 2012 and Angeloni and Faia 2013). Most of these papers are however solved via a first order approximation of the system around the steady state, thus assuming that financial constraints are binding at any point in time.

Recently, however, some papers have investigated the properties of models à la Gertler and Karadi (2011) assuming that financial frictions are only occasionally binding: Bocola (2014) is a paper very close to mine in terms of modelling, although its focus is on the effects of sovereign default risk on lending behavior. Prestipino (2014) also relies on a similar non-linear set up, although the policy focus is not on preventive macroprudential policies but on *ex-post* bail-outs.

The second strand of literature is related to solving and estimating non-linear DSGE models with financial frictions. In this respect the paper most close in spirit is Guerrieri and Iacoviello (2015a). In that paper, the authors use the solution method discussed above for solving and estimating a DSGE with an occasionally binding collateral constraint on housing and a zero lower bound for the policy rate. They however estimate the model via maximum likelihood, whereas this paper makes use of a more general estimation method, that can be in principle applied to any non-linear model.

The rest of the paper is organized as follows. In Section 3.2 the key ingredients of the model are introduced. In Section 3.3 the solution of the model is presented along with the estimation strategy. In Section 3.4 the model is actually brought to the data and the results discussed. In Section 3.5 I introduce macroprudential policies and perform counterfactual exercises. Section 3.6 concludes.

3.2 The Model

The model builds on a standard New Keynesian DSGE framework, enrichred with a financial sector à la Gertler and Karadi (2011). In this model, households provide labor services to the production sector but do not directly hold physical capital. Instead, the financing of production is intermediated by banks, which get funded by a combination of households' bank loans and internal equity and invest in both loans to firms and in government bonds. The production sector is made of intermediate good producers, capital producers and retailers. The distinction between intermediate good producers and capital producers is introduced in order to have a real friction in investment, which is subject to adjustment costs. Retailers are instead introduced in the model to keep nominal frictions separated from the rest of the model. As the household and production sides of the economy are relatively standard I leave a more accurate description of these sectors to Appendix 3.7. In what follows, I will mainly focus on the banking sector and on government policies.

The banking sector

I assume that the representative household is made of a fraction of workers while the remaining part is made of bankers. Each banker runs a bank. In each period a fraction $1-\sigma$ of bankers becomes workers within the family and is replaced by an equal fraction of workers that become bankers. The new bankers are endowed with funds provided by the household.

In each period t, the funds available to a banker are bank loans d_t that are bought by workers and real net worth n_t, which arises from past earnings (for surviving bankers) and from endowments from the household (for new bankers). A banker uses these resources to buy private assets (loans) k_t at price $p_{k,t}$,[6] and long-term government bonds b_t at price $p_{b,t}$. The balance sheet of a banker then writes

$$p_{k,t}k_t + p_{b,t}b_t = n_t + d_t. \tag{3.1}$$

At the end of period t returns from the two assets are accrued and are used to repay the bank loans. The leftover is the net worth of the banker which accumulates according to the following law of motion

$$n_t = (1 + r_{k,t})\, p_{k,t-1}k_{t-1} + (1 + r_{b,t})p_{b,t-1}b_{t-1} - [1 + (1 - \tau_d)r_{d,t-1}]\, d_{t-1} \tag{3.2}$$

where $r_{k,t}$, $r_{b,t}$ and $r_{d,t}$ are respectively the returns on firms' loans, on government bonds and on bank loans. Note that here I allow for the possibility of introducing a tax on debt (τ_d) which for the moment is set to zero but

[6] The loans to the real economy are in fact a financial instrument that resembles more an equity contract (Gertler and Karadi, 2011).

whose role will be highlighted at a latter stage when policy experiments will be conducted.

The banker's objective is to maximize the discounted value of its net worth:

$$v_t = E_t \left\{ \sum_{s=1}^{\infty} \beta^s \frac{\lambda_{t+s}}{\lambda_t} (1-\sigma) \sigma^{s-1} n_{t+s} \right\}.$$

Up to this point, the introduction of a banking sector does not give rise to financial frictions per se and does not alter the dynamics of this economy. The financial friction is therefore introduced in the form of a minimum regulatory capital requirement. More precisely, it is assumed that the banking regulator requires that the discounted value of the bankers' net worth should be greater or equal than the current value of assets, weighted by their relative risk. Hence, denoting with $\alpha \in (0,1]$ the risk weight on loans to the real economy and with $\alpha\alpha_b \in (0,1]$ the risk weight for government bonds, the regulatory constraint writes:

$$v_t \geq \alpha(p_{k,t}k_t + \alpha_b p_{b,t} b_t). \tag{3.3}$$

To solve the banker's problem we adopt a guess and verify approach. We guess that the value function is a linear object of the form $v_t = \gamma_t n_t$, where γ_t can be interpreted as the marginal value of an extra unit of net worth. Then we can rewrite the value function as

$$v_t = \max_{k_t, b_t} E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} \Omega_{t+1} n_{t+1} \right\}$$

subject to constraint (3.3), with $\Omega_t \equiv 1 - \sigma + \sigma\gamma_t$. Hence the first order conditions for k_t and b_t and the complementary slackness condition read:

$$\beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \Omega_{t+1} \left[r_{k,t+1} - (1-\tau_d)\, r_{d,t} \right] \right\} = \alpha\mu_t \tag{3.4}$$

$$\beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \Omega_{t+1} \left[r_{b,t+1} - (1-\tau_d)\, r_{d,t} \right] \right\} = \alpha\alpha_b\mu_t \tag{3.5}$$

$$\mu_t \left[\gamma_t n_t - \alpha \left(p_{k,t} k_t + \alpha_b p_{b,t} b_t \right) \right] = 0 \tag{3.6}$$

where μ_t is the multiplier for constraint (3.3). The multiplier can be interpreted as the shadow value of relaxing the credit constraint. Therefore, it is also a measure of the severity of the financial friction. Indeed, note that when the constraint is not binding (i.e. $\mu_t = 0$), we get that $r_{k,t} = r_{b,t} = r_{d,t-1}$ so that the financial friction is shut down and the frictionless economy allocation is recovered.[7] Another interpretation of the constraint being not binding is that when $\mu_t = 0$ the economy is in a Modigliani-Miller setup: it is indeed indifferent for the bank to hold equity and debt, as their rate of return is equivalent.

Another useful remark is the following. In the light of our guess of the value function, we can rewrite (3.3) as follows

$$n_t \geq \varphi_t \left(p_{k,t} k_t + \alpha_b p_{b,t} b_t\right) \tag{3.7}$$

where $\varphi_t = \frac{\alpha}{\gamma_t}$ has a straightforward interpretation as a capital ratio. In other words, in order to comply with regulatory requests, the bank needs to keep this ratio at a level at least equal to φ_t.[8]

As in Bocola (2014) and in Prestipino (2014), but in contrast with the original contribution by Gertler and Karadi (2011), I do not impose that the constraint is binding all the time. I treat it instead as an occasionally binding constraint, thus introducing a relevant non-linearity in the model.

To see the relevance of such assumption, in Figure 3.2 the amount of bankers' net worth along with the difference (in logs) between the left and the right-hand sides of inequality (3.7) is plotted.

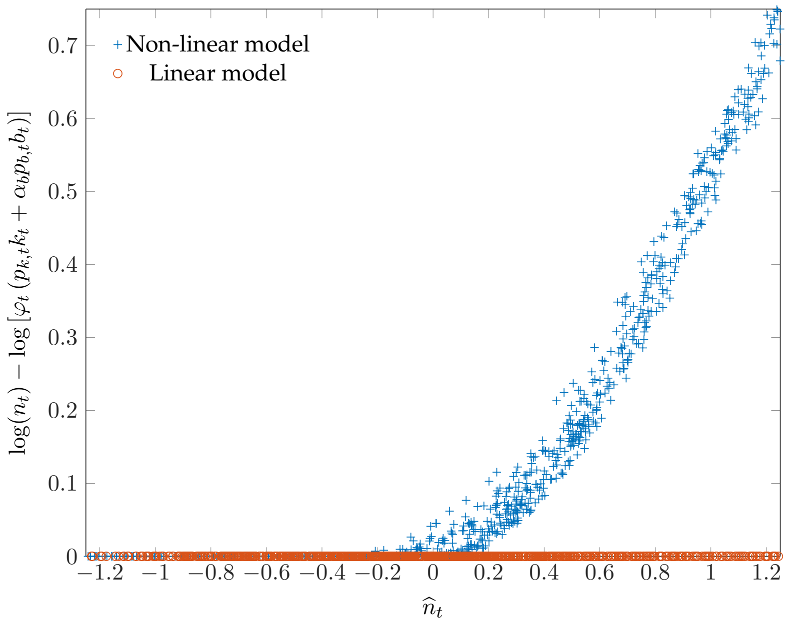
More precisely, Figure (3.2) draws from a simulation of the model, with parameters values equal to the ones resulting from the calibration and estimation exercises conducted in the following sections. On the horizontal axis I plot bankers' net worth in log-deviation from the steady state. On the vertical axis I plot inequality (3.7) in logs. If the constraint was always binding, the difference between the left and the right hand sides of inequality (3.7) would be zero as the net worth of bankers would always equate the right hand side of the equation. This is indeed what actually happens when the model is linearized around the steady state (linear model).

If the model is solved assuming that the constraint is binding only occasionally, instead, there are times in which the net value of bankers exceeds the minimum level required by the regulator. An interesting feature of the non linearity is that when the constraint is not binding the relationship between the net worth of banks and the amount of assets held (ie. the amount of loans to the economy and of government bonds) is less stringent. This occurs more often when banks are well capitalized. In other words, the probability of the constraint being slack is higher with high values of $\widehat{n}_t$.

[7] Throughout this section I set for simplicity $\tau_d = 0$.

[8] We assume that capital regulation is perfectly enforceable and cannot be circumvented.

Figure 3.2: Occasionally binding credit constraint



Note: This figure plots data from a simulation of the model for 1000 periods. It displays on the horizontal axis the value of n_t in long-deviation from the steady state, while on the horizontal axis the log of both sides of the inequality (3.7). The values of the parameters are the ones derived from the results of the calibration and estimation exercises discussed in the following sections.

The above described features of this environment can be recovered also in Bocola (2014) and in Prestipino (2014). The main difference with these papers is however that for the solution and estimation of the model I rely on methods that allow to deal with several shocks and frictions, thus effectively estimating a medium scale non-linear DSGE model with a large number of parameters.

Turning back to the solution of the bankers' problem, if we substitute equation (3.2) and the FOCs into the value function we get

$$v_t = \alpha\mu_t \left(p_{k,t}k_t + \alpha_b p_{b,t} b_t\right) + \beta \frac{\lambda_{t+1}}{\lambda_t} \Omega_{t+1} \left[1 + (1-\tau_d) r_{d,t}\right] n_t$$

then using FOCs and the guess for the value function we can recover the value of γ_t:

$$\gamma_t n_t = \gamma_t \mu_t n_t + \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \Omega_{t+1} \left[1 + (1-\tau_d) r_{d,t}\right] n_t \right\}$$

$$\gamma_t = \frac{1}{1-\mu_t}\left[\beta E_t\left\{\frac{\lambda_{t+1}}{\lambda_t}\Omega_{t+1}\left[1+(1-\tau_d)r_{d,t}\right]\right\}\right]. \tag{3.8}$$

In the first expression it can be seen that the marginal value of an extra unit of net worth can be decomposed into two terms: the return on equity when the constraint is not binding and the gain that comes from relaxing the regulatory capital constraint.

The description of the banking sector is concluded by constructing the aggregate law of motion for the net worth of the banking sector as a whole. Aggregate net worth is made of the sum of the net worth of old and new bankers, weighted by their number. The old bankers' net worth is given by combining (3.1) and (3.2). As for new bankers, their net worth is given by their endowment. We assume that the transfer to new bankers is proportional to the beginning of period net worth n_{t-1}, with proportionality coefficient ω. On aggregate, the law of motion of real net worth n_t is thus

$$\begin{aligned} n_t = \; & \sigma\left[(r_{k,t}-r_{d,t-1})p_{k,t-1}k_{t-1}+(r_{b,t}-r_{d,t-1})p_{b,t-1}b_{t-1}\right] \\ & +\left[\sigma(1+(1-\tau_d)r_{d,t-1})+\omega\right]n_{t-1}. \end{aligned}$$

Government

The government finances its public expenditure by raising taxes and issuing long term bonds. Long-term bonds are modeled assuming that in each period only a fraction δ_π of them comes to maturity. On the remaining fraction of bonds the government pays instead a coupon ρ. In order to introduce sovereign risk in the model, we assume that the fraction of short-term bonds may be subject to the shock $\varphi_{b,t}$. Such a shock implies a reprofiling of debt maturity: in case of a negative shock, the government is unexpectedly lengthening the maturity structure of its bond stock and partly postponing the reimbursements of short term bonds, thus implying a partial default. Then, denoting $\tilde{\delta}_\pi = \delta_\pi e^{\varphi_{b,t}}$, the government budget constraint writes

$$p_{b,t}\left[b_t-(1-\tilde{\delta}_\pi)b_{t-1}\right] = b_{t-1}\left[\tilde{\delta}_\pi+(1-\tilde{\delta}_\pi)\rho\right]+g_t-Tax_t,$$

where the return on bonds will be equal to

$$1+r_{b,t} = \frac{\tilde{\delta}_\pi+(1-\tilde{\delta}_\pi)(\rho+p_{b,t})}{p_{b,t-1}}e^{\varphi_{b,t}}.$$

Total taxes are equal to

$$Tax_t = T_t+\tau_c c_t+\tau_w w_t h_t+\tau_d r_{d,t-1}d_{t-1}.$$

where T is a lump sum tax, τ_c is a consumption tax, τ_w is a tax on labor and τ_d is a tax on deposits. We assume that government spending obeys the fiscal rule[9]

$$\widehat{g}_t = \gamma_g \widehat{g}_{t-1} + \lambda_g \widehat{b}_t + \varphi_{g,t}$$

where $\widehat{g}_t$ and $\widehat{b}_t$ denote log-deviations from the steady state and $\varepsilon_{g,t}$ is a disturbance to government spending.

Monetary policy is captured by a simple Taylor rule

$$i_t = \rho_{mp} i_{t-1} + (1 - \rho_{mp}) \left[\frac{\kappa_\pi}{4} \hat{\pi}_t^a + \frac{\kappa_y}{4} (\log y_t - \log y_{t-4}) \right] + \varphi_{R,t}$$

where $1 + \pi_t^a = \prod_{p=0}^{3} (1 + \pi_{t-p})$ and

$$1 + i_t = (1 + r_{d,t}) \, E_t (1 + \pi_{t+1}).$$

In counterfactual experiments, we will allow for a time varying tax on bank debt and to a richer specification of the Taylor rule.

3.3 Model solution and empirical strategy

Solution of the model

One of the key challenges of the model is related to the non-linearity of the system and to the related intractability for estimation purposes. Dealing with a large non-linear model is still considered a daunting task for practitioners: accurate methods such as those grouped under the label of "global methods" are usually computationally intensive and can only deal with rather few state variables.[10]

For models with occasionally binding constraints, an interesting alternative to these methods has been recently put forward by Guerrieri and Iacoviello (2015b). The basic intuition behind the suggested method is to approximate the policy functions via a first-order piecewise linear approximation around the steady state of the model. The method builds on the fact that models with an occasionally binding constraint can be summarized by two regimes: one in which the constraint is binding and the other in which

[9] To ensure the stationarity of bond dynamics, an endogenous fiscal rule is needed as shown in Bohn (1995).

[10] This is one of the main differences of this paper with Bocola (2014), where global methods are used in the solution of the model. This implies that in that paper estimation has to be performed in two steps, given the high computational burden.

the constraint is not binding.[11] The linearization of each regime is performed around the steady state, using a guess-and-verify approach to identify the transition path from one regime to the other. The interested reader can find an accurate description of the algorithm along with the minimal properties of the model required for applying the method in the original paper by Guerrieri and Iacoviello (2015b).

An important assumption for the solution method to work is that in the long run, in absence of shocks, the model has to return to its unique non-stochastic steady state. In the present paper, we assume that the steady state exists and is located in the regime where the financial constraint is binding. When we will discuss the actual calibration and estimation of the model, we will check that the value of the multiplier at steady state is effectively greater than zero (ie. the constraint is binding). [12]

The solution of the current model, under the proposed method, can be written as

$$X_t = P\left(X_{t-1}, \varepsilon_t\right) X_{t-1} + Q\left(X_{t-1}, \varepsilon_t\right) \varepsilon_t \tag{3.9}$$

where X_t is the vector of endogenous variables - both jump and predetermined - while ε_t is the vector of the structural shocks. It can be seen that the non-linearity of the model is preserved also in this first-order approximation since the transition matrices P and Q are time-varying.

Estimation strategy

The solution technique discussed above poses a challenge in terms of estimation, since the likelihood of the system - although in principle observable - is computationally hard to recover. In principle one could still make use of maximum likelihood methods to estimate the system of equations (3.9). Indeed, this is what Guerrieri and Iacoviello (2015a) do when they bring their model to the data. However, in what follows I explore a more general estimation procedure that could in principle fit any non-linear DSGE model. To the best of my knowledge, this is one of the first papers where this method is employed for estimating a DSGE.[13] For the model at hand, the estimation

[11] The argument can be made more general in case of more than one occasionally binding constraint.

[12] Note however that this is an unrequired step in the procedure, as the linearization under the two regimes could be performed around a different point.

[13] A New Keynesian model in continuous time is estimated with this technique in Hayo and Niehof (2014), while a more general discussion of this method in DSGEs, with an application to the Zero Lower Bound is Scalone (2015).

procedure I propose is equivalent in terms of computation time to estimating the model via maximum likelihood.

The method belongs to the class of likelihood-free methods and is called Adaptive Bayesian Computation (ABC, see Beaumont et al. 2002). In essence, the ABC method builds on an MCMC sampler, whose acceptance/rejection criterion is given by the distance of a given set of simulated moments from their empirical counterparts.

This method has two main advantages compared to other methods. First, alike to the Simulated Method of Moments it implies that one does not need to compute the likelihood of the system. This is particularly useful when the likelihood is not available or hard to compute. Secondly, and in opposition to the Simulated Method of Moments, since the ABC is a Bayesian method, one can make use of priors to inform the exploration of the space of parameters. This is a huge practical advantage, since priors can be easily derived from the literature or - as I do in the actual estimation of the model at hand - from the estimation of a linear version of the model (for example assuming that the constraint is always binding). More discussion of the estimation method can be found in Appendix 3.8.

3.4 Implementation and data

Turning to the actual implementation, the total number of parameters in the model is 42. I split the set of parameters into two subsets. A first subset of 23 parameters is recovered via calibration of steady state values. A discussion of the calibration of these parameters as well as the actual value of the parameters is reported in the next section. The remaining 19 parameters are estimated. I run draws of parameters values using as priors the results of a maximum likelihood estimation on a linear model where I assume that the regulatory constraint is always binding.[14]

The data used in the estimation are seven Italian macroeconomic series taken at quarterly frequency in the period 1999q1 to 2014q4. We take real per-capita consumption, GDP and investment. For inflation we take the Harmonised Index of Consumer Prices. We then take three series for interest rates: the bank bonds rate R_d is the average rate on bank bonds, the return on physical capital R_k is represented by the interest rate on loans to non-financial corporations, while the interest rate on government bonds R_b is an index produced by the Bank of Italy known as "Rendistato". This index is the average yield on a basket of government securities weighted by their

[14] The prior values for this preliminary linear estimation are taken from Cahn et al. (2014).

outstanding amount. All the series are detrended with a one-sided HP-filter with smoothing parameter set at 1600.

The set of moments I use for estimation is dictated by the fit of the linear version of the model at hand. More precisely, I first estimate the linear version of the model in order to recover prior values for the ABC estimation phase. Then I simulate the linear model and compute a long list of moments: the variance of the above seven series, their correlation, 1st and 2nd order autocovariances. Of this large set of moments, I retain for the ABC estimation phase only those whose sign is correctly identified by simulated data from the linear model. I therefore end up with 23 moments to be matched (see Table 3.3).

Calibration

A subset of 23 parameters is calibrated in such a way that the steady-state value of some variables matches the average in the period 1999-2014 of their empirical counterparts. The parameter values are reported in Table 3.1.

The discount factor β is set to 0.991 in order to match the annual Italian banking sector average yield on bonds of 3,68% between 1999 and 2014.[15] The inverse of the Frisch elasticity of labor supply is instead fixed at 2, a value that is standard in a vast macro literature (eg. see Smets and Wouters 2007). The degree of habit formation and the parameter for adjustment costs in investment are taken from the estimation performed by Cahn et al. (2014) (CMS from now on).

Then, I set parameters for the adjustment cost function reported in equation (3.12): a_0 is chosen to obtain a normalized steady state capital utilization of 1, while the value for a_1 is taken from CMS. The scale parameter for labor supply, χ, is chosen to match a steady state value for labor equal to .33, as is standard in the literature. The depreciation rate δ and the capital share in the production function, θ, are also assigned standard values.

The values for parameters related to the nominal rigidity block are taken from CMS. Among those, the product elasticity of substitution is set at a level that implies a price markup of 20 per cent, while firms are assumed to be able to reoptimize their prices once every three quarters.

Turning to parameters related to the banking sector, the survival rate for bankers, which implies an average length of life of a banker of about 16 years, is taken from CMS. The risk weight parameter α is instead chosen to match the annual Italian banking sector average yield on loans to the non-financial

[15] Indeed, at the steady state the following relationship holds: $1 = (1 + R_d)\beta$.

Table 3.1: Calibration values

Parameter	Value	Description
β	0.991	discount factor
η	0.55	degree of habit formation
ζ	2	inverse of Frisch elasticity of labor supply
ν_i	3.31	investment adj. costs
a_0	.035	utilization cost parameter
a_1	.41	utilization cost parameter
χ	9192	labor supply scale parameter
δ	.025	depreciation rate
θ	.3	capital share
Nominal rigidity parameters		
θ_p	6	product elasticity of substitution
ξ_p	.66	price reoptimization probability
ι_p	.17	degree of inflation indexation
Banking sector parameters		
σ	.985	bankers survival rate
α	0.18	risk weight on loans
α_b	1.1368	relative risk weight on bonds
$\hat{\omega}$	0.00065	new bankers' endowments
Fiscal parameters		
τ_c	.061	consumption tax
τ_w	.082	labor tax
δ_π	.0412	share of short-term government bonds
ρ	0.005	coupon on long-term bonds
Steady state values		
b/y	3.7	steady state debt-to-gdp ratio
g/y	0.19	steady state share of government consumption
π	0	steady state inflation

sector. Such a yield was equal to 3,94 per cent on an annual basis between 1999 and 2014. The parameter governing the relative risk of government bonds as compared to the loans to firms, α_b, is also taken to match the average interest rate on Italian government bonds from 1999 to 2014. Such a rate is the Rendistato yield, which on average was equal to 3,98 per cent in the reference period. Lastly, the parameter related to the endowment of new bankers, $\hat{\omega}$, targets the average capital ratio for Italian banks from 1999 to 2014, equal to 11.5 per cent.[16] Note in passing, that such calibration of banking sector parameters implies that the multiplier at steady state is positive ($\mu = 0.005$), thus implying that the reference regime is the one in which the financial constraint is binding.[17]

Moving to fiscal parameters, the value for τ_c corresponds to the average amount of VAT as a percentage of GDP (6.1 per cent). The value of the labor tax parameter τ_w corresponds to the revenue of labor taxation (for employed paid by employees) as a percentage of GDP (8.2 per cent). The source for these values is Eurostat (2014). As for parameters related to government bonds, the share of short-term government bonds, δ_π, is chosen to match the average residual life (6,07 years) of bonds traded on the MTS market, the most relevant trading venue for Italian government bonds (source: Bank of Italy). The coupon paid on long term issuances, ρ, is instead set to a value that matches the average coupon on BTPs issued from 1999 to 2014 (1,95% a year, source: Italian Treasury).

Two steady state relationships are also imposed: the debt to GDP ratio is set at 3.7, which is the equivalent at a quarterly frequency of the average debt-to-GDP per year in Italy 1999-2014 (92.5 per cent). The ratio of government spending over GDP is instead set at the value of 19 per cent, as in the data. These two ”great ratios” are computed based on data from the Italian quarterly national accounts, provided by Istat. The amount of government debt is computed as the outstanding amount of general government securities (source: Bank of Italy). Lastly, inflation at the steady state is set for simplicity (and in line with the literature) at zero per cent.

[16] The capital ratio series is available from the IMF at a semiannual frequency from 1999 to 2011 and is given by the ratio of total regulatory capital over risk-weighted assets. For more recent years I make use of quarterly data from the Bank of Italy.

[17] Detailed computations of the steady state of the model are reported in a Technical Appendix, available upon request.

Estimation Results

The estimation chain is made of 100,000 draws with an acceptance rate equal to 21.7%. The results of the estimation are reported in Table 3.2.

Table 3.2: Estimation Results

Parameter	Prior shape	Prior mean (linear model)	Prior s.d.	Posterior mean (non-linear model)	Posterior s.d.
κ_π	gamma	2.1996	0.3	1.6201	0.3621
κ_y	gamma	1.0137	0.1	0.7134	0.1325
λ_g	beta	-0.6065	1	-1.8541	0.8498
ρ_c	beta	0.3317	0.15	0.3575	0.1010
ρ_k	beta	0.0816	0.15	0.0653	0.924
ρ_i	beta	0.2216	0.15	0.2761	0.1132
ρ_z	beta	0.5807	0.15	0.6067	0.0956
ρ_b	beta	0.7655	0.15	0.7796	0.0893
ρ_g	beta	0.9899	0.15	0.7372	0.2140
ρ_r	beta	0.3865	0.15	0.4012	0.1008
γ_g	beta	0.2165	0.15	0.2272	0.1060
ρ_{mp}	beta	0.3029	0.15	0.3163	0.1043
σ_c	inv. gamma	0.0314	2	0.0234	0.0248
σ_k	inv. gamma	0.0308	2	0.0216	0.0182
σ_i	inv. gamma	0.0529	2	0.0383	0.0285
σ_z	inv. gamma	0.0308	2	0.0234	0.0150
σ_b	inv. gamma	0.1524	2	0.1000	0.0566
σ_g	inv. gamma	0.0362	2	0.0211	0.0140
σ_r	inv. gamma	0.0306	2	0.0495	0.0323

Note: This table reports the estimated values of parameters under an Adaptive Bayesian Computation algorithm based on 100,000 draws from prior distributions. The values for priors are retrieved from a ML estimation of the linearized model, assuming that the credit constraint is always binding. The prior means for this preliminary linear estimation are derived from Cahn et al. (2014).

Estimated parameters can be grouped in two subgroups: the first is related to policy parameters, namely the coefficients of the Taylor rule and the endogenous response of government spending to public debt. The second subgroup is made of parameters related to the shocks in the economy. First, it is interesting to note that Taylor rule parameters have significantly lower values in the non-linear model. This may be due to the fact that in order to match the big swings observed in the data, in the linear model a more aggressive monetary policy is required. On the other hand, the parameter related to the endogenous component in the fiscal rule takes a much higher value in absolute terms in the non-linear version of the model.

The remaining parameters are the autoregressive parameters and the standard deviations of the shocks. Concerning the former, it is interesting to note that the autoregressive parameters are basically confirmed both in the linear model (ie. the prior) and in the non-linear one, whereas the variances of these shocks tend to differ in the two models. More precisely, we find that the value of most of the variances turns out to be lower in the non-linear version of the model (with the exception of the variances of the confidence and of capital quality shocks). This suggests that part of the exogenous variation in the linear model is endogenized in the non-linear version. In other words, the non-linear model is better able to endogenously generate business cycle fluctuations, whereas the linearized model needs to rely more on external disturbances to match the big swings observed in the data.

In Figure 3.3 we plot the estimated multiplier, along with the filtered series of output, in log-deviation from its steady state.[18]

The multiplier is greater than zero in 33 quarters, thus implying that the constraint is binding almost half (52%) of the time. The multiplier reached its highest value in 2009Q1, in correspondence with the Lehman crisis. It is found to be binding also during the sovereign debt crisis (in 2011-2012) and after the burst of the dot-com bubble, in 2002, in conjunction with a slowdown in output growth.

Matching moments

Turning to moments matching, in Table 3.3 we plot the values of the moments used in the estimation exercise both in the data and in the linear model.

The non-linear model represents a significant improvement in terms of variance matching compared to its linear counterpart. This comes at the expense of matching correlations among the selected variables, whereas the performance in terms of matching autocorrelations (with one or two lags)

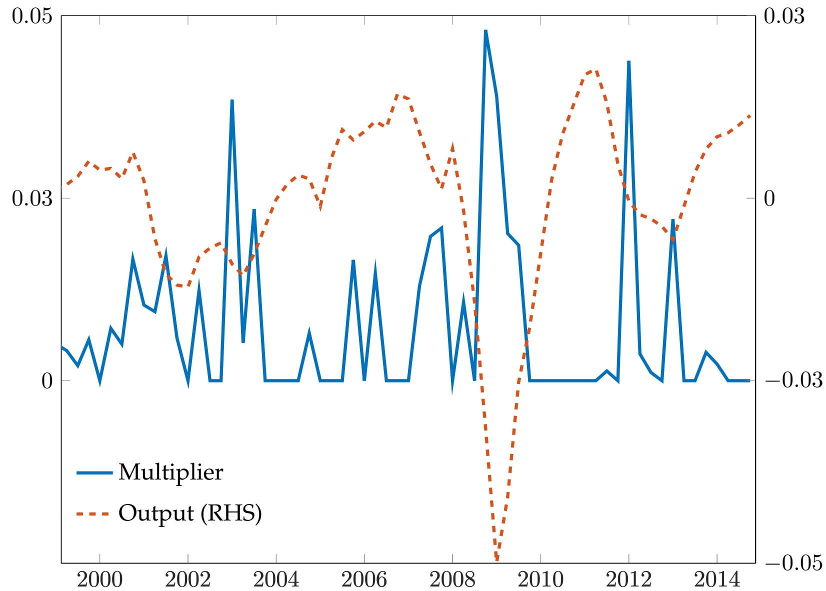
[18]The filtered series for output is obtained as follows. First, filtered shocks are recovered applying a standard Kalman smoother around the linearized model (using as observables output, consumption, investment and inflation) with parameters values equal to the posterior mean, assuming that the constraint is always binding. Then the series of shocks is introduced into the non-linear model and solved with the method of Guerrieri and Iacoviello (2015b).

Table 3.3: Empirical and Simulated Moments

Moment		Data	Non-linear model	Linear model
Standard deviation	y	1.28	1.27	5.57
	c	1.20	1.68	6.40
	i	2.58	6.32	36.99
	R_d	0.36	2.90	13.77
	R_b	0.57	6.87	43.49
	R_k	0.64	8.74	45.44
	π	0.67	2.12	7.73
Correlation	y, i	0.91	0.58	0.79
	y, π	0.37	0.69	0.60
	c, R_b	0.51	-0.05	0.10
	c, R_k	0.50	-0.01	0.10
	i, π	0.39	0.08	0.27
	R_b, R_k	0.65	0.88	0.97
First order autocovariance	y	0.89	0.73	0.85
	c	0.66	0.53	0.72
	i	0.84	0.93	0.96
	R_d	0.64	0.85	0.90
	R_b	0.82	0.98	0.98
	R_k	0.59	0.95	0.94
	π	0.92	0.49	0.43
Second order autocovariance	y	0.75	0.07	0.03
	R_k	0.83	0.38	0.38
	π	0.58	0.15	0.14

This table reports the value of the moments used in the estimation of the model. The estimated moments for the linear and non-linear models are computed via a simulation for 1,000 periods of the two models, with parameters values taken from the estimation above described. The values of R_d, R_b,R_k and π are annualized. Standard deviation for each series is multiplied by 100.

Figure 3.3: Estimated Multiplier and Output



This figure plots the filtered value of the multiplier (left-hand scale) along with the actual dynamics of output (right-hand scale).

is relatively similar in the linear and non-linear models. The importance of solving the model non-linearly can be gauged when one moves to higher order moments. What the non-linear version of the model adds is indeed an asymmetric behavior of variables in boom and bust periods. This can be observed in Figure 3.4 where we plot the density of output both in the data and in a 1,000 period simulation of the two models.

It can be noted that the distribution of output in the data displays a fat left tail, which is mainly associated to the 2009 slump. The linear model approximates the density pretty badly, due to the fact that linear models are by definition symmetric.

The above fact is more rigorously tested in Table 3.4, where I report skewness and kurtosis of output, consumption and investment in the two versions of the model and in a simple VAR(1), with parameters values as in the preceding section and simulating the model for 1,000 periods.

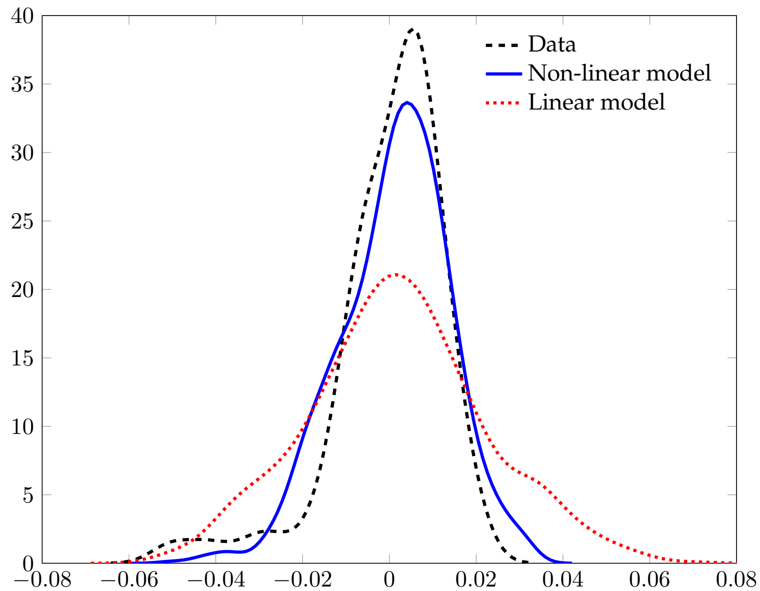
It can be noticed that with respect to output and investment, the non-linear model is the only one that is able to accurately match the negative skewness of the two distributions, thus confirming the quantitative relevance of the occasionally binding constraint, that induce asymmetric cycles with

Table 3.4: Asymmetry of real variables

	Output	Consumption	Investment
	Skewness		
Non-linear model	-0.42	-0.40	-1.59
p-value	*$<$ 0.1%*	*$<$ 0.1%*	*$<$ 0.1%*
Linear model	-0.21	-0.11	-0.19
p-value	*7.15%*	*34.93%*	*11.24%*
VAR(1)	0.11	0.12	-0.01
p-value	*33.76%*	*30.75%*	*94.01%*
Data	**-1.70**	**-0.54**	**-1.19**
p-value	***0.26%***	***22.42%***	***1.90%***
	Kurtosis		
Non-linear model	3.42	3.22	5.06
p-value	*1.6%*	*16.7%*	*$<$ 0.1%*
Linear model	3.02	3.19	3.09
p-value	*81.28%*	*21.87%*	*49.07%*
VAR(1)	2.93	2.99	2.93
p-value	*72.24%*	*97.89%*	*71.46%*
Data	**6.90**	**3.27**	**4.72**
p-value	***0.05%***	***40.26%***	***1.95%***
	Deepness (Triples test)		
Non-linear model	-5.33	-4.40	-40.12
p-value	*$<$ 0.1%*	*0.11%*	*$<$ 0.1%*
Linear model	-1.86	-0.03	0.48
p-value	*6.31%*	*97.85%*	*63.11%*
VAR(1)	1.15	0.62	-0.11
p-value	*25.12%*	*53.73%*	*90.93%*
Data	**-2.81**	**-1.69**	**-2.53**
p-value	***0.5%***	***9.13%***	***1.13%***

Note: This table reports skewness, kurtosis and ”deepness” of output, consumption and investment computed from a simulation for 1,000 periods of the models, with parameters values taken from the estimation described in the text, and from the data. The numbers in italic are the p-values for the D'Agostino test (for skewness) and of the Anscombe test (for kurtosis). The null hypotesis for the D'Agostino test is that skewness is not significantly different from zero. The null hypothesis for the Anscombe test is that kurtosis is not significantly different from 3 (as in the normal distribution). The Jarque-Bera test has the null hypothesis that the series is normally distributed. The null hypotesis for testing deepness has that the data are symmetrically distributed about an unknown median.

Figure 3.4: Output density



Note: In this figure the densities of output, consumption and investment both in the data and in the models are reported. Density is computed through a normal kernel smoothing estimate over 100 equally spaced points. The density for the linear and non-linear models is computed via a 1,000 periods simulation of the models, with parameters values taken from the estimation and calibration exercises above described.

crisis episodes being deeper than booms. Consumption is instead found not to be significantly skewed in the data (and in the linear models). Such finding can be easily explained with the the desire of households to smooth consumption over the business cycle. The non-linear DSGE produces a figure for consumption skewness not so distant from the one in the data, although the null hypothesis is rejected.

Turning to kurtosis, the data reveal that output and investment display a leptokurtic distribution, thus implying a higher peak and longer tails compared to the normal distribution. These features of the data are confirmed in the non-linear model, whereas they are rejected in the linear models.

As a last robustness check on the asymmetric distribution of the data, I perform a non-parametric test developed by Randles et al. (1980) known as the Triple test. The test aims at identifying ”deepness” of the data, which intuitively can be defined as a feature that emerges when in the series the troughs of the cycles are deeper than its peaks are tall (Razzak, 2001). Its null hypothesis is that the distribution is symmetric about an unknown median. The outcome of this test on the data confirms the previous findings on skewness: output and investment data are found to possess depth (or negative asymmetry) at a 5% level. Such feature of the data is captured by the non-linear model, but not by the linear models.

3.5 Counterfactuals with macroprudential policies

In this section we build on the estimation results to quantitatively assess the impact of macroprudential policies on the real economy. Here macroprudential policies are introduced as three different tools. First of all, I introduce a Countercyclical Capital Buffer (CCyB) in the banking sector. The CCyB can be viewed as the main macroprudential tool of the Basel III regulatory framework and it is aimed at ensuring "that banking sector capital requirements take account of the macro-financial environment in which banks operate" (BCBS, 2011). In practical terms, it implies that the regulatory capital ratio should increase during the positive phase of the financial cycle, in order to make the banking sector more resilient.

In theory, however, a direct intervention in the banking system, is not the only macroprudential policy option available. Indeed, after the Great Financial Crisis of 2008 new streams of literature have been explored (and old streams of literature revived) investigating the role of more standard tools, such as monetary and fiscal policies, in stabilizing the financial cycle. On the monetary policy side, a fierce debate started on whether it is appropriate for monetary policy to take into account financial conditions in the Taylor rule or not (see for example Gambacorta and Signoretti 2014). It has also been observed that fiscal policy can play and active role in mitigating the effects of the financial cycle via Pigouvian taxation (Jeanne and Korinek 2010). I therefore will introduce in the current setting, as potential alternatives to the countercyclical capital buffer, a enriched version of the Taylor rule and a tax on excessive banks leverage, with the aim of quantitatively investigating the behavior of these various policies through the cycle.

Therefore I will focus on the following three tools.

Countercyclical capital buffer

I introduce the countercyclical capital buffer assuming that the banking regulator can make the capital requirement procyclical and dependent on the credit-to-gdp gap (CGG). This policy tool has indeed a real-life counterpart in the Countercyclical Capital Buffer introduced in Basel III.[19] Specifically, I assume that under this policy the α parameter in equation 3.7 is not fixed anymore, but varies through the cycle according to the following formula:

$$\alpha_t = \alpha + \lambda_\alpha \widehat{CGG}_t$$

where $\widehat{CGG}_t$ is defined as in Basel III as current credit to the economy (k_{t-1}) divided by the average GDP in the last 4 quarters, net of the trend:

$$\widehat{CGG}_t = \frac{k_{t-1}}{0.25\sum_{i=1}^{4} y_{t-i}} - \frac{k}{y}.$$

In what follows λ_α is set at the value 1.5, which implies that the countercyclical add-on can reach a maximum value of about 2.5% in the simulation exercises. This is indeed the maximum value of the buffer envisaged in the Basel III accords.

Countercyclical fiscal policy

As an alternative to the countercyclical capital buffer, I assume that the policymaker can tame the financial cycle via the introduction of a time-varying tax on bank debt, which is linked to the growth of the credit-to-GDP gap as follows:

$$\tau_{d,t} = \tau_d + \lambda_d \widehat{CGG}_t.$$

This policy has no immediate real-life counterpart, but has been proposed by several academics and policymakers as a way of reducing the overall level of systemic risk in the economy (Kashkari, 2016). One can think of it as a policy wedge that is introduced with the aim of discouraging excessive credit to the real economy. The policy works through the asset pricing equations that determine the supply of credit (equations 3.4 and 3.5). An increase in the leverage tax leads to higher interest rates on loans to the real economy and government debt, thus leading to a tightening of credit supply and an overall reduction in new lending. As for the calibration of such instrument, in the following simulations we set the parameter λ_d at .9, thus implying a maximum tax/subsidy rate equal to about 10% across the cycle. However, we also perform some sensitivity analysis on alternative values of λ_d. Note that the introduction of a leverage tax is partly akin to a capital requirement in our model, since they both influence the cost of lending.

[19] See http://www.bis.org/bcbs/basel3.htm.

Leaning-against-the-wind monetary policy

As a last option, the credit-to-GDP gap is introduced as an extra variable in the Taylor rule:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[\frac{\kappa_\pi}{4}\hat{\pi}_t^a + \frac{\kappa_y}{4}(\log y_t - \log y_{t-4}) + \lambda_i \widehat{CGG}_t\right] + \varphi_{R,t}.$$

Such an extended policy rule and its stabilization properties have been extensively studied both at a theoretical level and at a quantitative one[20] and it is a policy that has been employed by central banks to tackle bubbles in some asset markets.[21] The parameter λ_i is assigned the value of 0.05, which implies that the risk free rate is raised by up to 2% (at an annual frequency) in the boom phase of the credit cycle.

Effectiveness of policies under different shocks

As a first step, I will consider the effects of the different policies taking each shock in isolation. In what follows I therefore analyze the behavior of some relevant variables in a setting where I artificially generate a boom-bust episode with a sequence of positive realizations of a shock followed by a sequence of negative realizations of the same shock.

The path I will simulate is for the capital quality shock, assuming twelve periods of growth followed by twelve periods of abrupt, negative values for the shock. The capital quality shock, as introduced in Gertler and Karadi (2011), has a straightforward interpretation as a pure financial shock that affects the return from capital investment. As can be seen in Figure 3.5, the shock sequence induces a growth in real variables such as output, consumption and investment, with a long lasting recession following the realization of negative shocks.

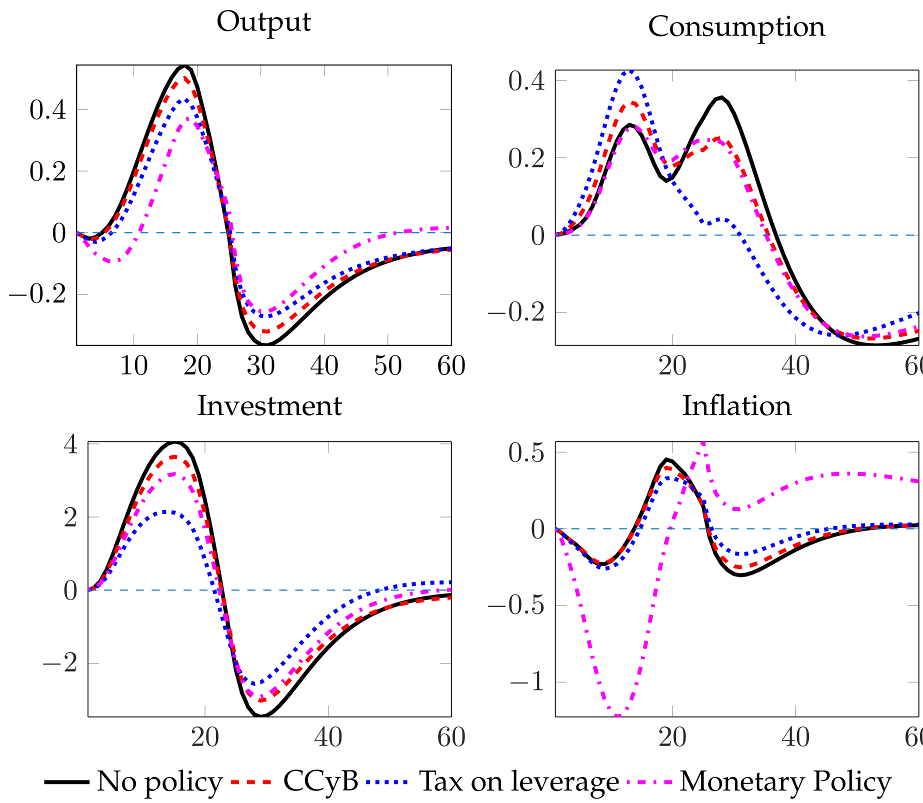
The simulation assumes that the economy starts from the steady state, where the credit friction is binding. The occurence of several positive shocks induces a relaxation of the constraint, which becomes not binding, as can be gauged by the dynamics of the multiplier in Figure 3.6.

Then, the bust phase induces a sudden tightening of the constraint. In terms of effectiveness of policies, it can be noted that the introduction of a countercyclical element in monetary policy leads to the most pronounced

[20]See *ex multis* Curdia and Woodford (2010), Cúrdia and Woodford (2015) and Gambacorta and Signoretti (2014).

[21]A recent case that has been intensely debated is the one of Sweden, where the Riksbank in recent years has pursued a relatively restrictive monetary policy in order to reduce risks stemming from the housing market (Svensson, 2016).

Figure 3.5: Response to a capital quality shock

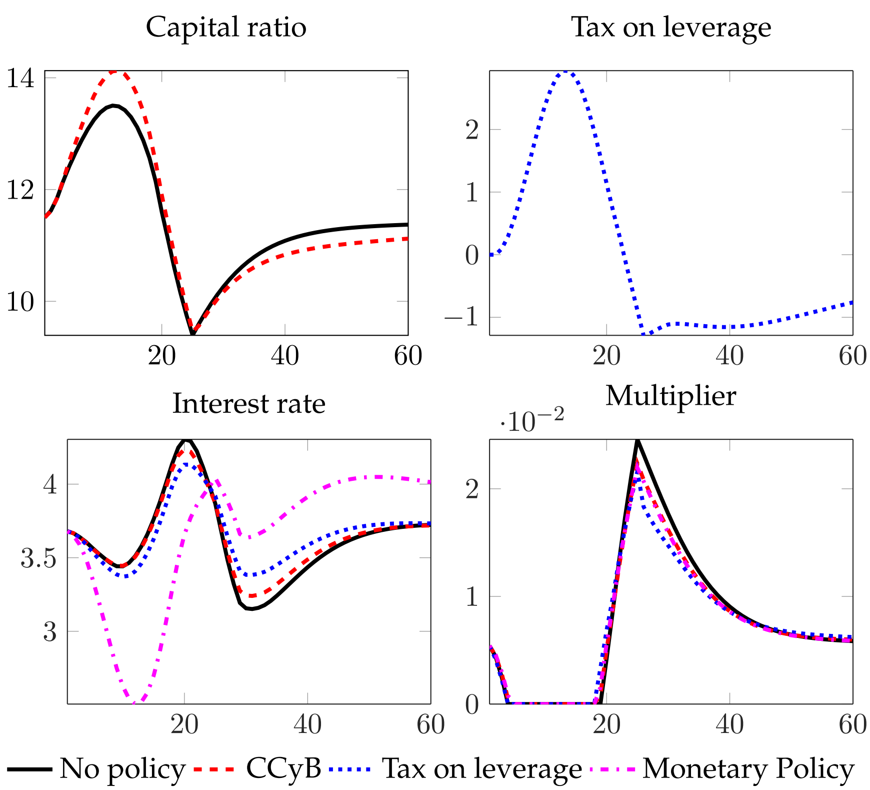


Note: This figure displays the response of output, consumption and investment to a sequence of capital quality shocks under different policy scenarios in deviation from the "no policy" case. Values are in per cent. Inflation is converted at annual values.

impact on output: it reduces its growth in the boom phase and smooths out its fall in the crisis episode, with a faster return to the steady state.

On the other hand, the introduction of a countercyclical capital buffer does not seem to play a significant role in the boom phase, while it slightly attenuates the financial friction - and thus mitigates the fall in investment - in the bust phase. This is indeed a key result that can be gauged only with a non-linear model. Indeed, part of the reason for the ineffectiveness of the CCyB lies in the fact that the CCyB is a policy that directly targets the regulatory constraint of bankers. However, in "good times" this constraint is not binding and thus the behavior of bankers during this period is not directly affected by the policy. The CCyB has nonetheless an indirect effect on the real economy even when the constraint is not binding, via the expectations of the

Figure 3.6: Policy response to a capital quality shock



Note: This figure displays the response of different policy tools to a sequence of capital quality shocks. The interest rate is converted at annual frequency. The values for the capital ratio, the tax on leverage and on the interest rate are in per cent.

agents concerning the intensity of the credit friction in future periods. Such an indirect effect seems however rather limited in the quantitative analysis.

At the same time, in times of crisis the existence of a countercyclical capital buffer provides two benefits in terms of financial frictions. In the first place, the bankers enter in the crisis with a higher level of net worth compared to the "no policy" case. Second, the policy, as constructed in the model, implies that in the crisis period the credit constraint is relaxed (ie. the value of α falls below its steady state level) thus implying that less net worth is required to provide funding to the real economy and this relaxes the intensity of the credit friction.

Turning to the impact on consumption and investment, a rather different picture emerges when considering fiscal policy vis-à-vis monetary policy and the CCyB. Fiscal policy seems to be most effective in smoothing investment, but this comes at the expenses of consumption, which is slightly hampered at the trough of the crisis.

Lastly, inflation reacts in a significant way only when monetary policy is actively fighting the credit cycle. This is a side effect of monetary policy and highlights the dilemma faced by a central bank that aims at simultaneously targeting both inflation and excessive credit growth.

The dynamics of policy variables during this boom-bust episode can be gauged in Figure 3.6. In the CCyB regime the capital ratio is enriched of a countercyclical add-on that reaches a maximum of 0.5% during the boom phase. The accumulation of this buffer implies that when a series of negative shocks hits, the financial sector has more net worth compared to the baseline scenario and thus it can cope with a slightly higher capital ratio. The reason is that under the CCyB regime, during crisis times the marginal value of an extra unit of net-worth may be lower than in the baseline scenario. Thus when a CCyB is in place, the capital ratio evolves partly because of the mechanical effect of the CCyB and partly because of an endogenous response of γ_t, the marginal value of bankers' net worth.

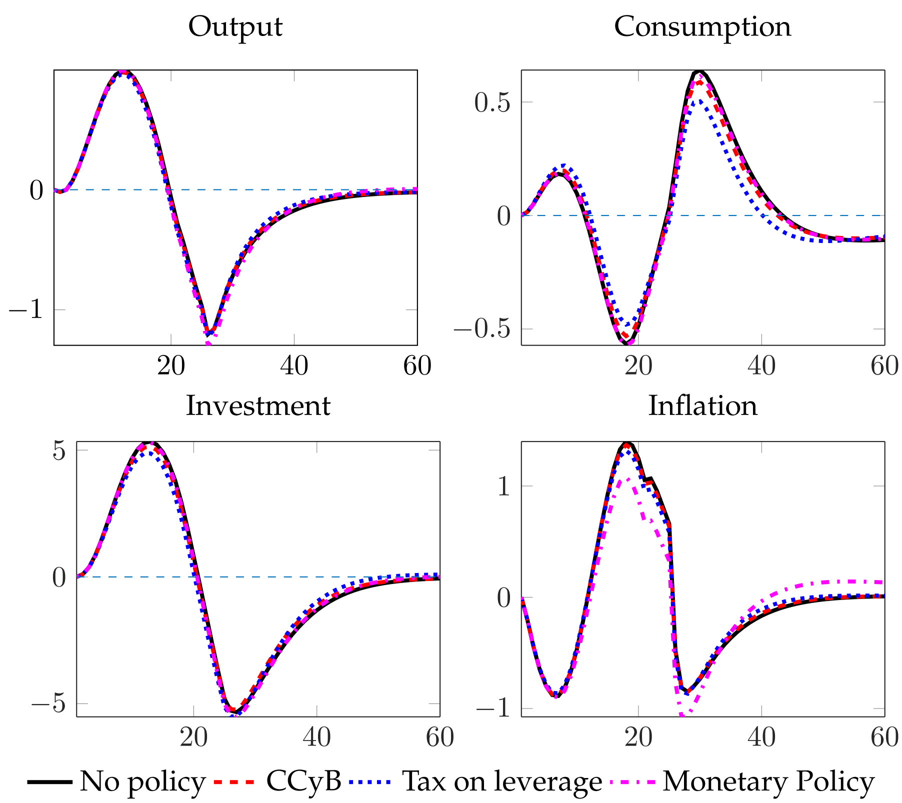
Alternatively, the policymaker can let the tax on leverage vary with the credit-to-gdp gap. The dynamics of the tax is reported in the second panel of the Figure. It can be noted that the tax is increasing (up to 3%) during the boom and becomes a transfer in the crisis period. Lastly, the dynamics of the risk free rate are reported. Interestingly, adding an extra term in the Taylor rule implies that the interest rate tends to be lower in booms and higher in busts, mainly as a result of the endogenous response of inflation. Also, note that the response of the interest rate is highly asymmetric in boom and bust. Note also that fiscal policy affects the interest rate, while the CCyB does not.

The above described responses however are heavily dependent on the kind of shock hitting the economy. In other words, the policy tools above described can be effective only when the cycle is driven by shocks directly related to the accumulation of capital. If the boom and the subsequent bust is driven by other forces, the tools can prove less effective. Indeed, suppose that the economy is hit by a different shock, say a productivity shock (see Figure 3.7).

In this case, policies are very much ineffective in contrasting such dynamics and the simple reason behind this result is that productivity is a variable that does not directly enter in the reaction function of the policymaker.

Hence, several conclusions can be drawn from these experiments. First, monetary policy when enriched of a countercyclical component, can be prove rather effective in smoothing output dynamics. On the other hand, due to the inner nature of the non-linearity, the countercyclical capital buffer is less ef-

Figure 3.7: Response to a productivity shock



Note: This figure displays the response of output, consumption and investment to a sequence of productivity shocks under different policy scenarios in deviation from the "no policy" case. Values are in per cent.

fective. Also, the effectiveness of all of the above policies is highly dependent of the shocks hitting the economy. Quantitatively, these policies prove more effective when the economy is hit by financial shocks that directly affect the banking sector.

Counterfactuals

In this section I will investigate the features of our economy under the baseline case and in the three policy counterfactuals. In order to do so, I simulate the model for 1000 periods with no macroprudential policies in place. Then I use the same shock sequence from the baseline case in three conterfactual experiments, in each of which I activate a distinct macroprudential policy. I then compute some features of interest of these economies, such as the variance of real variables (output, consumption and investment), the number of periods spent with binding financial frictions and the length of a period with financial frictions.[22] I also report two variables that capture the severity of the financial frictions, which are represented by the mean value of the multiplier in those periods when the multiplier is positive and the maximum value reached during the simulation. In Table 3.5 all these variables are reported along with their percentage deviation from the baseline.

Table 3.5: Counterfactuals

Feature	Baseline (A)	CCyB (B)	Dev. % (B)-(A)	Fiscal Policy (C)	Dev. % (C)-(A)	Monetary Policy (D)	Dev. % (D)-(A)
$V(y)$	1.62	1.55	**-4.1%**	1.45	**-10.5%**	1.51	**-7.0%**
$V(c)$	2.82	2.72	**-3.3%**	2.09	**-25.9%**	2.32	**-17.7%**
$V(i)$	39.94	34.88	**-12.7%**	22.80	**-42.9%**	31.26	**-21.7%**
Crisis times (%)	24.60	24.00	**-2.4%**	24.90	**1.2%**	24.20	**-1.6%**
Length crisis	7.03	6.15	**-12.4%**	5.08	**-27.7%**	5.63	**-19.9%**
Mean severity	0.94	0.90	**-4.5%**	0.90	**-5.0%**	0.89	**-5.5%**
Max severity	11.52	11.03	**-4.2%**	11.11	**-3.5%**	11.40	**-1.0%**

Note: This table reports various features of the model under various macroprudential measures. The features have been computed from a simulation of the model for 1000 periods under the same shocks. Variances are multiplied by 100. The length of a crisis period is in quarters. The severity of the crisis is measured as the value of the multiplier (multiplied by 100). The columns Dev. % represent the percentage deviation of the outcome under each policy with respect to the outcome in the baseline (ie. without macroprudential policies) scenario.

In the table it can be seen that output volatility is reduced by all three policies. Fiscal policy however seems the most effective policy in reducing volatility of real variables, whereas the least effective policy in reducing volatility appears to be the CCyB.

The economy has financial frictions in place for about 25 per cent of the time and no macroprudential policy seems able to significantly reduce such number. However, the average length of the crisis (which in the baseline is about 7 quarters) is shortened up to 5 quarters with a fiscal policy actively fighting excessive credit. Lastly, the severity of the frictions - measured in terms of the average and the maximum values of the multiplier - is also re-

[22]Here I define a period in which financial frictions are binding as a period of financial stress. For brevity, in Table 3.5 I will label such episodes as ”crisis” episodes.

duced under active macroprudential policies, but only modestly.[23]

In Appendix 3.10, some sensitivity analysis is performed with respect to different values of the policy parameters λ_α, λ_d and λ_i. The exercise shows that a significant increase of the policy parameters most of the time leads to a reduction in volatility and in the severity of the crisis, although the gains are relatively modest. Interestingly, raising the coefficient of the CCyB implies that the economy stays in a financial crisis more frequently, due to the fact that it is more likely fro the banking sector to hit the regulatory constraint. Also, with respect to monetary policy, a stronger reaction of the interest rate implies an increase in output volatility.

Overall, two main takeaways should be taken from the counterfactual exercise. First, macroprudential policies seem indeed effective in smoothing business cycle dynamics. Second, fiscal policy seems to be the most effective policy, although there is no single dominating policy, since all of them tackle different aspects of the dynamics induced by binding financial frictions. Fiscal and monetary policies display a better overall performance compared to the countercyclical capital buffer, which may be partly attributed to the specific calibration of the Basel III buffer, but also to the mechanisms through which the effects of this policy tool propagate through the economy.

3.6 Conclusion

In this paper I investigated the quantitative properties of various macroprudential policies and their impact on the real economy. I made use of the method of Guerrieri and Iacoviello (2015b) for solving the model with a non-linearity arising from the presence of an occasionally binding credit constraint. I then showed how to estimate the model with likelihood-free methods. I further showed that the non-linear model is able to generate relevant asymmetries in the dynamics of output and investment that cannot be obtained with linear models.

The results of the estimation are then used for performing counterfactual exercises assuming that various macroprudential policies are in place. It is shown that the activation of these policy tools can indeed reduce business cycle fluctuations and that the most effective tool implies altering the cost of

[23] It has to be noted that the analysis carried so far is exclusively focussed on the transmission on the real economy of macroprudential policy stimulus. However, since no bank default will ever occur in equilibrium, the model is agnostic on whether the CCyB increases the resilience of the banking sector. For a model of macroprudential policies in which default in the banking sector is explicitely modelled, see Clerc et al. (2015).

leverage for the banking sector, making leverage more costly in boom periods and subsidizing it in times of crisis.

Further research could be in the future devoted to the study of interactions and complementarities of various macroprudential policies in a nonlinear environment, and to performing welfare analyses aimed at identifying the optimal instruments among the many available and their optimal parameterization.

3.7 Appendix: Rest of the model

Households

There is a continuum of measure one of identical households. In each household there is a fraction of bankers f, while the other members of the household are workers. There is perfect consumption insurance between workers and bankers. A typical household has the utility function

$$E_t \sum_{s=0}^{\infty} \beta^s e^{\varphi_{c,t+s}} \left\{ \log(c_{t+s} - \eta c_{t+s-1}) - \frac{\chi}{1+\zeta} \int_0^{1-f} h_{t+s}(i)^{1+\zeta} \mathrm{d}i \right\} \qquad (3.10)$$

where c_t is private consumption. The flow of consumption services is subject to habit formation, with degree $\eta \in [0,1)$, $h_t(i)$ is the supply of labor of each worker in the household, $\chi > 0$ is a scale parameter, and $\zeta \geq 0$ governs the elasticity of labor supply. Finally, $\varphi_{c,t}$ is a preference shock that follows a zero-mean AR(1) process of the form

$$\varphi_{c,t+1} = \rho_c \varphi_{c,t} + \sigma_c \epsilon_{c,t+1}, \quad \epsilon_{c,t} \sim N(0,1).$$

The household maximizes (3.10) subject to the sequence of real budget constraints

$$(1+\tau_c)c_t + d_t = (1 + r_{d,t-1})d_{t-1} + (1-\tau_w)w_t h_t + Div_t + T_t \qquad (3.11)$$

where w_t is the real wage rate paid to worker *i* and d_t denotes deposits paying the real interest rate $r_{d,t}$. Taxes are levied on the household in the form of a lump sum tax T_t and of taxes on consumption (τ_c) and on labor (τ_w). Finally Div_t denotes net aggregate profits redistributed by retailers, intermediate good firms, capital producers, and bankers to the households. Let λ_t denote the Lagrange multiplier on constraint (3.11).

Intermediate Good Production

At the end of period $t-1$, a unit-mass continuum of intermediate good firms finances capital purchases to be used in the next period by issuing k_{t-1} which are bought by bankers at price $p_{k,t-1}$. At the beginning of period t the quality of capital is revealed to the firms through the realization of an AR(1) shock $\varphi_{k,t}$, so that efficient capital is $\bar{k}_t = \mathrm{e}^{\varphi_{k,t}} k_{t-1}$. In period t, these CRS firms have access to the technology

$$y_t = A(\upsilon_t \bar{k}_t)^{\theta} (e^{z_t} h_t)^{1-\theta},$$

where A is a scale factor, h_t is the input of aggregate labor, $\bar{k}_t$ is the input of efficient capital (i.e. capital after the capital quality has been revealed), and υ_t is the capital utilization rate, entailing a cost $a(\upsilon_t)\bar{k}_t$ (measured in final good units). The utilization cost is such that in the deterministic steady state $a(\upsilon) = 0$. We therefore assume that

$$a(\nu_t) = a_0(\nu_t - 1) + \frac{a_1}{2}(\nu_t - 1)^2, \tag{3.12}$$

Finally, z_t is a permanent productivity shock. Technical progress is assumed to evolve according to the process

$$z_t = z_{t-1} + \varphi_{z,t},$$

$$\varphi_{z,t+1} = \rho_z \varphi_{z,t} + \sigma_z \epsilon_{z,t+1}, \quad \epsilon_{z,t} \sim N(0,1).$$

Let $P_{m,t}$ be the price of the intermediate goods. Hence, profits obey

$$P_{m,t} A(\upsilon_t \bar{k}_t)^{\theta}(e^{z_t} h_t)^{1-\theta} - W_t h_t - a(\upsilon_t) P_t \bar{k}_t$$

The FOC wrt h_t and υ_t are

$$w_t = (1-\theta)\frac{P_{m,t}}{P_t}\frac{y_t}{h_t},$$

$$a'(\upsilon_t) = \theta \frac{P_{m,t}}{P_t}\frac{y_t}{\upsilon_t \bar{k}_t}.$$

Thus, the per-unit real cash flow accruing to effective capital $\bar{k}_t$ is

$$z_{k,t} = \theta \frac{P_{m,t}}{P_t}\frac{y_t}{\bar{k}_t} - a(\upsilon_t)$$

In equilibrium, the return on capital obeys

$$1 + r_{k,t} = \frac{z_{k,t} + (1-\delta)\, p_{k,t}}{p_{k,t-1}} e^{\varphi_{k,t}}.$$

This return is entirely rebated to banks to pay for the date $t-1$ loan.

Capital Producers

Capital producers buy back $\tilde{k}_t$ units old efficient capital units, add to these new capital units using the input of final output (subject to adjustment costs) and sell the new capital to firms at the relative price $p_{k,t}$. Given that households own capital producers, the objective of a capital producer is to choose a contingent plan for i_t so as to maximize

$$E_t \sum_{s=0}^{\infty} \beta^s \frac{\lambda_{t+s}}{\lambda_t} \left\{ p_{k,t+s} \left[\tilde{k}_{t+s} + i_{t+s} \left(1 - S\left(\frac{i_{t+s}}{i_{t-1+s}} \right) \right) e^{\varphi_{i,t+s}} \right] - i_{t+s} - p_{k,t+s} \tilde{k}_{t+s} \right\},$$

where $S(\cdot)$ is an adjustment cost function such that $S(1) = S'(1) = 0$. In the actual implementation of the model I will assume the following functional form for $S = \frac{\nu_i}{2} \left(\frac{i_t}{i_{t-1}} - 1 \right)^2$. The associated FOC on i_t is

$$1 = p_{k,t} \left(1 - S\left(\frac{i_t}{i_{t-1}} \right) - S'\left(\frac{i_t}{i_{t-1}} \right) \frac{i_t}{i_{t-1}} \right) e^{\varphi_{i,t}} + E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} p_{k,t+1} S'\left(\frac{i_{t+1}}{i_t} \right) \left(\frac{i_{t+1}}{i_t} \right)^2 e^{\varphi_{i,t+1}} \right\}.$$

Notice that the FOC on $\tilde{k}_t$ implies that any value of $\tilde{k}_t$ is consistent with profit maximization. It follows that $\tilde{k}_t$ is pinned down by the equilibrium on the market for used capital, yielding $\tilde{k}_t = (1-\delta)\mathrm{e}^{\varphi_{k,t}} k_{t-1}$, so that

$$k_t = (1-\delta)\, e^{\varphi_{k,t}} k_{t-1} + i_t \left(1 - S\left(\frac{i_t}{i_{t-1}} \right) \right) e^{\varphi_{i,t}}.$$

Retailers

Retailers simply repackage intermediate goods and sell it to the households. The final output composite writes

$$y_t = \left[\int_0^1 y_t(j)^{\frac{\theta_p - 1}{\theta_p}} \mathrm{d}j \right]^{\frac{\theta_p}{\theta_p - 1}}$$

Retailers face nominal rigidities à la Calvo, thus assuming that only a fraction $1 - \xi_p$ of them is allowed to adjust its resale price. If retailers cannot reoptimize, they update their prices according to the rule

$$P_{t+1}(i) = (1+\pi)^{1-\iota_p} (1+\pi_t)^{\iota_p} P_t(i)$$

Each retailer who is allowed to reoptimize chooses the price that the maximises the discounted value of profits until the price will remain fixed, subject to the demand constraint.

$$\max_{P_t^*(j)} \quad E_t \sum_{s=0}^{\infty} (\beta\xi_p)^s \frac{\lambda_{t+s}}{\lambda_t} \left[P_t^*(j)\Pi_{k=1}^s(1+\pi)^{1-\iota_p}(1+\pi_{t+k-1})^{\iota_p} - P_{mt+s}\right] y_{t,t+s}^*(j)$$

$$\text{s.t.} \quad y_t^*(j) = \left(\frac{P_t^*(j)}{P_t}\right)^{-\theta_p} y_t$$

Resource Constraint and Equilibrium

The aggregate resource constraint is

$$c_t + g_t + i_t + a(\upsilon_t)e^{\varphi_{k,t}}k_{t-1} = y_t.$$

3.8 Appendix: Estimation Strategy

The estimation implies performing an MCMC sampler where the acceptance/rejection criterion is given by a distance function of simulated moments from the empirical ones. As for priors I make use of the output of a Bayesian estimation from 500,000 draws of a first order approximation of the model where it is assumed that the constraint is always binding. In this way, I can make use of standard linear ML estimation techniques. Starting from these priors, I run the likelihood-free algorithm as described in the following subsection.

Some ingredients of the algorithms need a further clarification. First, the proposal distribution $q(\cdot, \theta_t)$ is a standard random walk proposal: $q(\cdot, \theta_t) \sim \mathbf{N}(\theta_t, c)$, where the variance-covariance matrix c is obtained as the inverse of the hessian of log-likelihood of linear model. Secondly, as for the weighting function $\pi_\varepsilon\left(y|x', \theta'\right)$ I make use of a Gaussian kernel density:

$$\pi_\varepsilon\left(y|x, \theta\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\rho(T(x),T(y))}$$

where $T(x)$ and $T(y)$ are respectively simulated and empirical moments. The function $\rho\left(T(x), T(y)\right)$ is instead the Mahalanobis distance between empirical and simulated moments:

$$\rho\left(T(x), T(y)\right) = \left\{\left[T(x) - T(y)\right]^\top W^{-1}\left[T(x) - T(y)\right]\right\}^{\frac{1}{2}}$$

where the weighting matrix W is a diagonal matrix whose diagonal elements are given by the absolute deviation (in percent) between the empirical moments and the moments generated by a 1,000 periods simulation of the linear model. In this way, the algorithm is automatically assigning less weight to the moments that the linear model is not able to accurately match.

Making use of the Gaussian kernel density has a practical advantage compared to other kernel density functions in that it does not require a bound for the maximum distance acceptable between $T(x)$ and $T(y)$ (see Sisson and Fan 2011).

As a last step, the vector of moments to be targeted is also extracted from a comparison between the data and the linear model. More precisely, the vector $T(.)$ is made of those moments whose sign is properly identified in a long simulation (1,000 times) of the linear model.

Estimation algorithm

The estimation algorithm is the following:

1. Initialize θ_1, $x_1(\theta_1)$

2. For steps $t = 1, ..., T$

   a) Generate θ' from the proposal distribution $q(\cdot, \theta_t)$

   b) compute $x' \sim \pi(x|\theta')$

   c) Calculate $r = \min\left\{1, \frac{\pi_\varepsilon(y|x',\theta')\pi(\theta')q(\theta',\theta_t)}{\pi_\varepsilon(y|x_t,\theta_t)\pi(\theta_t)q(\theta_t,\theta')}\right\}$

   d) Draw $u \sim U[0, 1]$

      i. if $u \leq r$ then $(x_{t+1}, \theta_{t+1}) = (x', \theta')$

      ii. else $(x_{t+1}, \theta_{t+1}) = (x_t, \theta_t)$

   e) Go back to step (a).

3.9 Appendix: Data Sources

- real per capita gdp, y: Source: Istat, quarterly national accounts.
- real per capita consumption, c: final consumption expenditure of households and non-profit institutions serving households. Source: Istat, quarterly national accounts.
- real per capita investment, i: gross fixed capital formation. Source: Istat, quarterly national accounts.
- rate on deposits, R_d: Banks: average yield on bonds - outstanding amounts. Source: Bank of Italy, Money and banking.
- rate on loans to firms, R_k: Bank interest rates on euro loans to non-financial corporations: new business. Interest rate - loans other than bank overdrafts to non-financial corporations - new business. Source: Bank of Italy, Money and banking.
- rate on government debt, R_b: Average gross yield-to-maturity on bonds in the sample of pubblic-sector securities, subject to withholding tax listed on the Stock Exchange (Rendistato). Source: Bank of Italy, The financial market.
- inflation rate, π: Harmonised Index of Consumer Prices. Source: ECB.

3.10 Appendix: Sensitivity Analysis

Table 3.6: Sensitivity of CCyB policy

λ_α	1	1.5	2	2.5	3
$V(y)$	1.57	1.55	1.53	1.52	1.50
$V(c)$	2.75	2.72	2.70	2.67	2.65
$V(i)$	36.46	34.88	33.40	32.01	30.72
Times in a crisis (%)	24.50	24.00	23.70	24.00	24.20
Length of a crisis (quarters)	6.28	6.15	5.78	5.71	5.76
Mean severity	0.91	0.90	0.89	0.88	0.87
max severity	11.06	11.03	10.99	10.95	10.90
Max φ	18.94	19.75	20.54	21.32	22.07
Median φ	14.48	14.63	14.73	14.79	14.88

Note: This table reports various features of the model under different values of λ_α. The features have been computed from a simulation of the model for 1000 periods under the same shocks. Variances are multiplied by 100. The length of a crisis period is in quarters. The severity of the crisis is measured as the value of the multiplier (multiplied by 100).

Table 3.7: Sensitivity of fiscal policy

λ_d	0.75	0.9	1.2	1.5	2
$V(y)$	1.47	1.45	1.43	1.41	1.40
$V(c)$	2.16	2.09	1.96	1.87	1.75
$V(i)$	23.96	22.80	21.45	21.02	21.57
Times in a crisis (%)	24.50	24.90	25.00	24.70	24.20
Length of a crisis (quarters)	5.10	5.08	4.55	4.26	4.25
Mean severity	0.90	0.90	0.89	0.88	0.88
Max severity	11.08	11.11	11.18	11.28	11.48
Max tax rate	9.30	10.87	13.83	16.62	21.00

Note: This table reports various features of the model under different values of λ_d. The features have been computed from a simulation of the model for 1000 periods under the same shocks. Variances are multiplied by 100. The length of a crisis period is in quarters. The severity of the crisis is measured as the value of the multiplier (multiplied by 100).

Table 3.8: Sensitivity of Monetary policy

λ_i	0.025	0.050	0.075	0.100	0.125
$V(y)$	1.50	1.51	1.63	1.85	2.18
$V(c)$	2.55	2.32	2.12	1.96	1.82
$V(i)$	35.19	31.26	28.12	25.79	24.24
Times in a crisis (%)	24.30	24.20	24.30	24.40	24.60
Length of a crisis (quarters)	5.93	5.63	5.06	4.98	4.64
Mean severity	0.92	0.89	0.87	0.84	0.82
Max severity	11.27	11.40	11.51	11.60	11.66

Note: This table reports various features of the model under different values of λ_i. The features have been computed from a simulation of the model for 1000 periods under the same shocks. Variances are multiplied by 100. The length of a crisis period is in quarters. The severity of the crisis is measured as the value of the multiplier (multiplied by 100).

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Chapter 4

Conclusion

The recent financial crisis has served as a reminder of the potential danger of ignoring the role of financial markets and of financial intermediaries and the relevance of informational frictions in shaping the decisions of economic agents. In this thesis we explored the above issues on several dimensions.

First, we highlighted the danger caused by undisciplined collateralized debt markets. In Chapter 1, we used home equity extraction as a case study to explore the distortions arising from *natural* expectations about future values of collateral. We showed that *natural* expectations arose during the period of the recent housing price boom because of the failure of households and financial experts to take into account the complex structure of house prices. We showed that agents may end up overestimating long-run prices if they make use of models that fail to capture the rich autocorrelation structure of housing prices and its mean-reverting component. While the notion that households are likely to misestimate house prices has been documented in the literature, in Chapter 1 we provided evidence that financial experts also were too optimistic about long-run prices before and during the recent house price boom. We showed the quantitative implications of *natural* expectations in a model where households and banks interact through a collateralized financial instrument. The model has then been fed with a set of expectations that differ in their ability to capture hump-shaped housing price dynamics. We documented that after a positive shock on housing prices, less *natural* agents expect a lower persistence of the shock. In contrast, natural agents overestimate the persistence of the process, thus leading to overly optimistic long-run forecasts. We then simulated the model by considering housing price dynamics as observed during the 2000s. Our models predict a positive relationship between the amount of home equity extracted in a boom phase and the degree of *naturalness* of the agents in the credit market, while at the same time stressing the prominence of banks' expectations in the equilibrium outcome. A version of the model in which agents hold *natural* expectations seems to capture the dynamics of U.S. home equity extraction during the recent boom and bust relatively well. Finally, we highlighted that financial experts *naturalness* is a crucial component for observing a large accumulation of debt at low interest rates.

Further, in Chapter 2 we highlighted the relationship between imperfect or "noisy" information and the conduct of fiscal policy. The role of imperfect information in business cycles is indeed one of the most promising research paths recently explored in macroeconomics. Using official forecasts of government spending as reported in the annual budgets of Canada, the UK and the US, we demonstrated the implementation of a limited information approach (a simple method of moments) to identify news and noise. The amount of noise observed for these three countries is significant: on average, the percentage of noise in official government spending forecasts ranges from 28% to 84%. Using these values in a richer DSGE setting, we highlighted the detrimental effects on fiscal multipliers, particularly on investment multipliers. Our approach can be fruitfully extended to other policy settings in which announcements play crucial roles, such as monetary policy (forward guidance) or banking regulations and structural reforms implemented with lags.

In Chapter 3 we investigated the quantitative properties of various macroprudential policies and their impact on the real economy. We made use of a new solution method for solving the model with a non-linearity arising from the presence of an occasionally binding credit constraint. We then showed how to estimate the model with likelihood-free methods. We further showed that the non-linear model is able to generate relevant asymmetries in the dynamics of output and investment that cannot be obtained with linear models. The results of the estimation are then used for performing counterfactual exercises assuming that various macroprudential policies are in place. It is shown that the activation of these policy tools can indeed reduce business cycle fluctuations and that the most effective tool implies altering the cost of leverage for the banking sector, making leverage more costly in boom periods and subsidizing it in times of crisis. Further research could be in the future devoted to the study of interactions and complementarities of various macroprudential policies in a non-linear environment, and to performing welfare analyses aimed at identifying the optimal instruments among the many available and their optimal parameterization.