WORKING PAPERS

N° 1065

January 2020

"Business Cycle Anatomy"

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Business Cycle Anatomy*

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January 17, 2020

Abstract

We propose a new strategy for dissecting the macroeconomic time series, provide a template for the propagation mechanism that best describes the observed business cycles, and use its properties to appraise models of both the parsimonious and the medium-scale variety. Our findings support the existence of a main business-cycle driver but rule out the following candidates for this role: technology or other shocks that map to TFP movements; news about future productivity; and inflationary demand shocks of the textbook type. Prominent members of the DSGE literature also lack the propagation mechanism seen in our anatomy of the data. Models that aim at accommodating demand-driven cycles under flexible prices appear promising.

*We thank the editor, Mikhail Golosov, and three anonymous referees for extensive feedback. For useful comments, we also thank Larry Christiano, Patrick Feve, Francesco Furlanetto, Jordi Galí, Lars Hansen, Franck Portier, Juan Rubio-Ramirez and participants at various seminars and conferences. Angeletos acknowledges the financial support of the National Science Foundation (Award #1757198). Collard acknowledges funding from the French National Research Agency (ANR) under the Investments for the Future program (Investissements d'Avenir, grant ANR-17-EURE-0010).

"One is led by the facts to conclude that, with respect to the qualitative behavior of co-movements among series, business cycles are all alike. To theoretically inclined economists, this conclusion should be attractive and challenging, for it suggests the possibility of a unified explanation of business cycles." Lucas (1977)

1 Introduction

In their quest to explain macroeconomic fluctuations, macroeconomists have often relied on models in which a single, recurrent shock acts as the main, or even the sole, driver of the business cycle.[1] This practice is grounded not only on the desire to offer a parsimonious, unifying explanation as suggested by Lucas, but also on the property that such a model may capture diverse business-cycle triggers if these share a common propagation mechanism: multiple shocks that produce similar impulse responses for *all* variables of interest can be considered as the same shock.[2]

Is there evidence of such a common propagation mechanism in macroeconomic data? And if yes, how does it look like?

We address these questions with the help of a new empirical strategy. The strategy involves taking multiple cuts of the data. Each cut corresponds to a VAR-based shock that accounts for the maximal volatility of a particular variable over a particular frequency band. Whether these empirical objects have a direct structural counterpart or not, their properties form a rich set of cross-variable, static and dynamic restrictions, which can inform macroeconomic theory. We call this set the "anatomy."

A core subset of the anatomy is the collection of the five shocks obtained by targeting the main macroeconomic quantities, namely unemployment, output, hours worked, consumption and investment, over the business-cycle frequencies. These shocks turn out to be interchangeable in the sense of giving rise to nearly the same impulse response functions (IRFs) for *all* the variables, as well as being highly correlated with one another.

The interchangeability of these empirical shocks supports parsimonious theories featuring a main, unifying, propagation mechanism. Their shared IRFs provide an empirical template of it.

In combination with other elements of our anatomy, this template rules out the following candidates for the *main* driver of the business cycle: technology or other shocks that map to TFP movements; news about future productivity; and inflationary demand shocks.

[1] E.g., this is the monetary shock in Lucas (1975), the TFP shock in Kydland and Prescott (1982), the sunspot in Benhabib and Farmer (1994), the investment shock in Justiniano, Primiceri, and Tambalotti (2010), the risk shock in Christiano, Motto, and Rostagno (2014), and the confidence shock in Angeletos, Collard, and Dellas (2018).

[2] To echo Cochrane (1994): "The study of shocks and propagation mechanisms are of course not separate enterprises. Shocks are only visible if we specify something about how they propagate to observable variables."

Prominent members of the DSGE literature also lack the propagation mechanism seen in the data, despite their use of multiple shocks and their good fit in other dimensions. Models that allow for demand-driven cycles in the absence of nominal rigidity, or when monetary policy replicates flexible-price allocations, hold promise.[3]

The empirical strategy. We first estimate a VAR (or a VECM) on the following ten macroeconomic variables over the 1955-2017 period: the unemployment rate; the per-capita levels of GDP, investment (inclusive of consumer durables), consumption (of non-durables and services), and total hours worked; labor productivity in the non-farm business sector; utilization-adjusted TFP; the labor share; the inflation rate (GDP deflator); and the federal funds rate. We next compile a collection of shocks, each of which is identified by maximizing its contribution to the volatility of a particular variable over either business-cycle frequencies (6-32 quarters) or long-run frequencies (80-∞). We finally inspect the empirical patterns encapsulated in each of these shocks, namely the implied IRFs and variance contributions.

The basic idea of identifying a shock by maximizing its variance contribution to a variable goes back to Uhlig (2003) and Faust (1998). What distinguishes our contribution is the multitude of such shocks considered, the empirical regularities recovered, and the lessons drawn for theory.[4] An additional contribution is that we draw a mapping from the frequency domain to the time domain: we show that shock that dominates the business-cycle frequencies (6-32q) of the key macroeconomic quantities is a shock whose footprint in the time domain peaks within a year or so.

Our approach also departs from standard practice in the SVAR literature, which aims at identifying empirical counterparts to specific theoretical shocks (for a review, see Ramey, 2016). Instead, it sheds light on dynamic comovements by taking multiple cuts of the data, one per targeted variable and frequency band. For example, one cut is obtained by targeting unemployment over the business-cycle frequencies, another by targeting TFP over the long-run frequencies, and so on. These multiple cuts, which may or may not have a direct structural interpretation, comprise our "anatomy" of the data and form a rich set of empirical restrictions that can discipline *any* theory, whether of the parsimonious type or the DSGE type.

The Main Business Cycle Shock. Consider the shocks that target any of the following variables over the business-cycle frequencies: unemployment, hours worked, GDP, and investment. These shocks are

[3] Recent examples of such models include Angeletos and La'O (2010, 2013), Bai, Ríos-Rull, and Storesletten (2017), Beaudry and Portier (2014, 2018), Beaudry, Galizia, and Portier (2018), Benhabib, Wang, and Wen (2015), Eusepi and Preston (2015), Jaimovich and Rebelo (2009), Huo and Takayama (2015), and Ilut and Saijo (2018). Related is also the earlier literature on coordination failures (Diamond, 1982; Benhabib and Farmer, 1994; Guesnerie and Woodford, 1993).

[4] An early version of our method appeared in Section 2 of Angeletos, Collard, and Dellas (2015); the present paper subsumes this earlier work.

interchangeable in terms of the dynamic comovements (IRFs) they produce. Furthermore, any one of them accounts for about three-quarters of the business-cycle volatility of the targeted variable and for more than one half of the business-cycle volatility in the remaining variables, and triggers strong positive co-movement in all variables. The shock that targets consumption is less tightly connected in terms of variance contributions, but still similar in terms of comovements/IRFs.

These findings offer support for theories featuring either a single, dominant, business-cycle shock, or multiple shocks that leave the same footprint because they share the same propagation mechanism. With this idea in mind, we use the term "Main Business Cycle shock" (henceforth, MBC shock) to refer to the common empirical footprint, in terms of IRFs, of the aforementioned reduced-forms shocks. This provides the sought-after template.

A central feature of this template is the interchangeability property, namely all the aforementioned reduced-form shocks produce essentially the same IRFs, or the same propagation mechanism. Below, we describe a few additional features of the MBC shock and of the overall anatomy, and discuss their lessons for theory. At first, we draw lessons through the perspective of single-shock models. Later, we switch to multi-shock models and discuss the challenges and the use of our method in such models.

Disconnect from TFP and from the long run. The MBC shock is disconnected from TFP at *any* frequency. It also accounts for little of the long-term variation in output, investment, consumption, and labor productivity. Symmetrically, the shocks identified by maximizing the long-term volatility in any of these variables make a negligible contribution to the business cycle.

These findings challenge not only with the baseline RBC model but also with models that map other shocks, including financial, uncertainty and sunspot shocks, into endogenous TFP fluctuations. Benhabib and Farmer (1994), Bloom et al. (2018) and Bai, Ríos-Rull, and Storesletten (2017) are notable examples of such models. In these models, the productivity movements over the business-cycle frequencies ought to be tightly tied to the MBC shock, which is not the case.

These findings also challenge Beaudry and Portier (2006), Lorenzoni (2009), and other works that emphasize signals ("news") of TFP and income in the medium to long run. If such news were the main driver of the business cycle, the MBC shock would be a sufficient statistic of the available information about future TFP movements, which is not the case. Instead, a semi-structural exercise based on our anatomy suggests that the contribution of TFP news to unemployment fluctuations is in the order of 10%, which is broadly consistent with the estimate provided by Barsky and Sims (2011).

The MBC shock fits better the notion of an aggregate demand shock unrelated to productivity and the long run, in line with Blanchard and Quah (1989) and Galí (1999). However, as discussed below, this shock ought to be non-inflationary, which may or may not fit the New Keynesian framework.

Disconnect from inflation. The shock that targets unemployment accounts for less than 10% of the fluctuations in inflation, and conversely the shock that targets inflation explains a small fraction of the unemployment fluctuations. A similar disconnect obtains between inflation and the labor share, a common proxy of the real marginal cost in the New Keynesian framework.

These properties preclude the interpretation of the MBC shock as an *inflationary* demand shock, of the type contained in the textbook, New Keynesian model. Could it be that the MBC shock represents a mixture of an inflationary demand shock and a disinflationary supply shock? While this possibility cannot be ruled out in general, it is invalid insofar as the supply shock is proxied by TFP in the data.

State-of-the-art DSGE models can fit these patterns by having an accommodative monetary policy generate realistic business cycles out of demand shocks, using a large degree of nominal rigidity to make sure that these shocks are nearly non-inflationary, and attributing the inflation fluctuations to large markup shocks. But the empirical micro-foundations of these models remain debatable.

A different possibility, which is accommodated by the models cited in footnote 3, is that the MBC shock represents a demand shock whose importance does not vanish when monetary policy replicates flexible-price outcomes. This possibility seems consistent not only with the aforementioned disconnect between inflation and real economic activity but also with with the fact that the MBC shock induces a strong countercyclical response in monetary policy, as measured by the federal funds rate.

The anatomy of medium-scale DSGE models. Our empirical strategy was motivated by parsimonious models. Does it retain it probing power in state-of-the-art, medium-scale DSGE models?

Such models pose a challenge for the interpretation and use of the identified MBC shock, as this may correspond to a combination of theoretical shocks, none of which individually has its properties.[5] But at the same time, such models give rise to a larger set of cross-variable, static and dynamic restrictions that can be confronted with our anatomy of the data.

We demonstrate these ideas in Section 6 using state-of-the-art, DSGE models. One is the sticky-price model of Justiniano, Primiceri, and Tambalotti (2010); this is essentially the same as that developed in Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). Another one is the flexible-price model found in an earlier paper of ours, Angeletos, Collard, and Dellas (2018); this is an extension of the RBC model that allows business cycles to be driven by variation in “confidence” and “news about the short-run economic outlook.” We view the former as representative of the New Keynesian paradigm

[5]This difficulty is not specific to our approach. It concerns any approach that requires a single shock to drive some conditional variance in the data. For instance, Galí (1999) requires that a single shock drives productivity in the long run, an assumption inconsistent with the literature on news shocks.

and the latter as an example of the literature cited in footnote 3, which aims at accommodating demand-driven business cycles outside the realm of nominal rigidities and Philips curves.

In each model, we perform an anatomy similar to that carried out in the data: we consider different linear combinations of the theoretical shocks, each one constructed by maximizing the business-cycle volatility of a different macroeconomic quantity. We then compare the model-based objects to their empirical counterparts.

Both models match the disconnect of the MBC shock from TFP and inflation. However, the first model have difficutly matching the interchangeability property of the MBC template: the reduced-form shocks obtained by targeting the key macroeconomic quantities are less similar in the model than their empirical counterparts. This is because this model, like many other members of the DSGE literature, attributes the business cycle to a fortuitous combination of specialized theoretical shocks, none of which generates the empirically relevant comovement patterns in the key macroeconomic quantities. By contrast, the second model fits the patterns seen in the data because it contains a dominant shock, or propagation mechanism, that alone generates these patterns.

As an additional demonstration of the value of our method, we use it to evaluate the model of Christiano, Motto, and Rostagno (2014). This model is a leader in a new strand of the DSGE literature that includes financial frictions and uses financial (risk) shocks to drive the business cycle. We find that this model, too, is subject to the challenge discussed above. It also misses some of the dynamic patterns seen in the data between the MBC shock, the credit spread and the level of credit.

To summarize: Although there is no presumption that the reduced-form objects comprising our anatomy can have a meaningful structural interpretation in the realm of arbitrary multi-shock models, they prove quite effective in the evaluation of the shock structure and propagation mechanisms in models actually used in the literature. And whether we interpret the evidence through the lenses of a parsimonious, single-shock perspective or through those of the state-of-the-art DSGE models considered, they seem to point in the direction of theories that aim at making sense of the idea that business cycles can be demand-driven even when monetary policy does a good job in stabilizing inflation and replicating flexible-price outcomes.

Layout. The rest of the paper is organized as follows. Section 2 describes the empirical method. Section 3 reviews our empirical findings. Section 4 reports various robustness exercises. Section 5 offers an interpretation of the main empirical findings. Section 6 contains the application to medium-scale models. Section 7 concludes.

2 Data and Method

The data used in our main specification consists of quarterly observations on the following ten macroeconomic variables: the unemployment rate (u); the real, per-capita levels of GDP (Y), investment (I), consumption (C); hours worked per person (h); labor productivity in the non-farm business sector (Y/h); the level of utilization-adjusted total factor productivity (TFP); the labor share ($\frac{Wh}{Y}$); the inflation rate (π), as measured by the rate of change in the GDP deflator; and the nominal interest rate (R), as measured by the federal funds rate. The sample starts in the first quarter of 1955, the earliest date of availability for the federal funds rate, and ends in the last quarter of 2017.

Following standard practice, and to ensure compatibility with the models used in Section 6, our measure of investment includes consumer expenditure on durables, while that of consumption consists of expenditure on non-durables and services. Both measures are herein deflated by the GDP deflator. Section 4.3 establishes the robustness of our results to the use of component-specific deflators; to different samples, such as the pre- and post-Volcker periods or excluding the Great Recession and the ZLB period; and to the incorporation of additional information, such as that contained in stock prices and financial variables. Appendix A contains the definitions and data sources.

We now turn to the description of the empirical method. As mentioned in the Introduction, the method involves running a VAR on the aforementioned ten variables and recovering certain "shocks." As in the SVAR literature, any of the shocks constructed here represents a particular linear combination of the VAR residuals. What distinguishes our approach is the criterion used in the identification of such a linear combination.

Let the VAR take the form

$$A(L)X_t = v_t,$$

where the following definitions apply: X_t is a $N \times 1$ vector, containing the macroeconomic variables under consideration; $A(L) \equiv \sum_{\tau=0}^{p} A_\tau L^\tau$ is a matrix polynomials in the backshift operator L, with $A(0) = A_0 = I$; p is the number of lags included in the VAR; and u_t is the vector of VAR residuals, with $E(u_t u_t') = \Sigma$ for some positive definite matrix Σ. Because of its large size, the VAR was estimated with Bayesian methods, using a Minnesota prior.[6] Also, our baseline specification set $p = 2$, which was the number of lags suggested by standard Bayesian criteria. Section 4.3 shows the robustness of our main findings to the inclusion of additional lags and the use of a VECM instead of a VAR.[7]

[6]The posterior distributions were then obtained using Gibbs sampling with 50,000 draws, and the reported highest posterior density intervals (HPDI) were obtained by the approach described in Koop (2003).

[7]A VECM may be recommended if the analyst believes, perhaps on the basis of theory, that certain variables are co-

We assume the existence of a linear mapping between the residuals, v_t, and some mutually independent "structural" shocks, ε_t, that is, we let

$$v_t = S\varepsilon_t$$

where S is an invertible $N \times N$ matrix and ε_t is i.i.d. over time, with $\mathbb{E}(\varepsilon_t \varepsilon_t') = I$. These "structural" shocks may or may no correspond to the kind of structural shocks featured in theoretical models; they are transformations of the VAR residuals, whose interpretation is inherently delicate.

We can always write $S = \widetilde{S}Q$, where $\widetilde{S}$ is the Cholesky decomposition of Σ, the covariance matrix of the VAR residuals, and Q is an orthonormal matrix, namely a matrix such that $Q^{-1} = Q'$. We then have that $\varepsilon_t = S^{-1}v_t = Q'\widetilde{S}^{-1}v_t$, which means that each one of the shocks in ε_t corresponds to a column of the matrix Q. Furthermore, Q satisfies $QQ' = I$ by construction, which is equivalent to S satisfying $SS' = \Sigma$. But this by itself does not suffice to identify any of the underlying shocks: additional restrictions must be imposed on Q in order to identify any of them. The typical SVAR exercise in the literature employs exclusion or sign restrictions motivated by specific theories. We instead identify a shock by the requirement that it contains the maximal share of all the information in the data about the volatility of a particular variable in a particular frequency band.

Let us fill in the details. The Wold representation of the VAR is given by

$$X_t = B(L)v_t$$

where $B(L) = A(L)^{-1}$ is an infinite matrix polynomial of the form $B(L) = \sum_{\tau=0}^{\infty} B_\tau L^\tau$. Replacing $v_t = \widetilde{S}Q\varepsilon_t$, we can rewrite the above as follows:

$$X_t = C(L)Q\varepsilon_t = \Gamma(L)\varepsilon_t,$$

where $C(L)$ and $\Gamma(L)$ are infinite matrix polynomials of the form $C(L) = \sum_{\tau=0}^{\infty} C_\tau L^\tau$ and $\Gamma(L) = \sum_{\tau=0}^{\infty} \Gamma_\tau L^\tau$, with $C_\tau \equiv B_\tau \widetilde{S}$ and $\Gamma_\tau \equiv C_\tau Q$ for all $\tau \in \{0, 1, 2, \ldots\}$. The sequence $\{\Gamma_\tau\}_{\tau=0}^{\infty}$ represents the IRFs of the variables to the structural shocks. This is obtained from the sequence $\{C_\tau\}_{\tau=0}^{\infty}$, which encapsulates the Cholesky transformation of the VAR residuals.

For any pair $(k, j) \in \{1, ..., N\}^2$, take the k-th variable in X_t and the j-th shock in ε_t. As already noted, this shock corresponds to the j-th column of the matrix Q. Let this column be the vector q. For any $\tau \in \{0, 1, \ldots\}$, the effect of this shock on the aforementioned variable at horizon τ is given by the (k, j) element of the matrix $\Gamma_\tau \equiv C_\tau Q$, or equivalently by the number $C_\tau^{[k]} q$, where $C_\tau^{[k]}$ henceforth denotes the k-th row of the matrix C_τ. Similarly, the contribution of this shock to the spectral density of this variable

integrated. But a VECM is also sensitive to the assumed co-integration relations, which explains why we, as much of the related empirical literature, use the VAR as our baseline specification.

over the frequency band $[\underline{\omega},\overline{\omega}]$ is given by

$$\Upsilon(q;k,\underline{\omega},\overline{\omega}) \equiv \int_{\omega\in[\underline{\omega},\overline{\omega}]} \left(\overline{C^{[k]}(e^{-i\omega})q}\,C^{[k]}(e^{-i\omega})q\right)\mathrm{d}\omega = q'\left(\int_{\omega\in[\underline{\omega},\overline{\omega}]} \overline{C^{[k]}(e^{-i\omega})}\,C^{[k]}(e^{-i\omega})\mathrm{d}\omega\right)q$$

where, for any vector v, $\overline{v}$ denotes its complex conjugate transpose.

Consider the matrix

$$\Theta(k,\underline{\omega},\overline{\omega}) \equiv \int_{\omega\in[\underline{\omega},\overline{\omega}]} \overline{C^{[k]}(e^{-i\omega})}C^{[k]}(e^{-i\omega})\mathrm{d}\omega$$

This matrix captures the entire volatility of variable k over the aforementioned frequency band, expressed in terms of the contributions of all the Cholesky-transformed residuals. It can be obtained directly from the data (i.e., from the estimated VAR), without any assumption about Q. The contribution of any structural shock can then be re-written as

$$\Upsilon(q;k,\underline{\omega},\overline{\omega}) = q'\Theta(k,\underline{\omega},\overline{\omega})q, \tag{1}$$

where, as already explained, q is the column vector of Q corresponding that shock.

The above is true for any shock, no matter how it is identified. Our approach is to identify a shock by maximizing its contribution to the volatility of a particular variable over a particular frequency band, that is, to choose q so as to maximize the number given in (1). It follows that q is the eigenvector associated to the largest eigenvalue of the matrix $\Theta(k,\underline{\omega},\overline{\omega})$.

This approach is similar to the "max-share" method developed in Faust (1998) and Uhlig (2003), and subsequently used by, inter alia, Barsky and Sims (2011) and Francis et al. (2014), except for two differences. First, we systematically vary the targeted variable and/or the targeted frequency band instead of committing to a specific such choice. That is, we provide multiple cuts of the data, instead of a single one, and draw lessons from their combination. Second, we identify shocks in the frequency domain rather than the time domain. This allows us, not only to adopt the conventional definition of what the business cycle is in the data, namely the frequencies corresponding between 6 and 32 quarters, but also to clarify how this maps to the time domain: targeting 6-32q in the frequency domain is *not* equivalent to targeting 6-32q in the time domain. We expand on this point in Section 4.2.

Our method also brings principle component analysis (PCA) to mind. Unlike it, however, our method allows for the recovery of IRFs, the evaluation of the relation between the short and the long run, and for multiple cuts of the data. We expand on this point in Section 4.1.

In the next section, we start by targeting unemployment and setting $[\underline{\omega},\overline{\omega}] = [2\pi/32, 2\pi/6]$, which is the frequency band typically associated with the business cycle (e.g., Stock and Watson, 1999). We then proceed to vary both the targeted variable and the targeted frequency band. This produces many different cuts of the data, the collection of which comprises the "anatomy" offered in this paper and forms the basis of the lessons we draw for theory.

3 Empirical findings

This section presents the main empirical findings and discusses a few tentative lessons for theory. These lessons are sharpest under our preferred perspective, namely, when seeking to understand the business cycle as the product of a single, dominant shock/mechanism. This is the perspective adopted in this section. Its relaxation in subsequent sections reveals the broader usefulness of our findings.

3.1 The Main Business Cycle Shock: Targeting Unemployment

A key finding in this paper is that the shocks that target the aggregate quantities over the business-cycle frequencies can be thought of as interchangeable facets of (what we call) the MBC shock. But as our anatomy consists of individual cuts of the data, we need to start with one of these shocks. We choose the shock that targets unemployment, rather than any of its "sister" shocks, because unemployment is the most widely recognized indicator of the state of the economy.

Figure 1 reports the impulse response functions (IRFs) of all the variables to this shock. As very similar IRFs are produced by the shocks that target the other key macroeconomic quantities, this figure plays a crucial role in our analysis: it serves as the empirical template for the propagation mechanism of models that contain a single or dominant business-cycle driver.

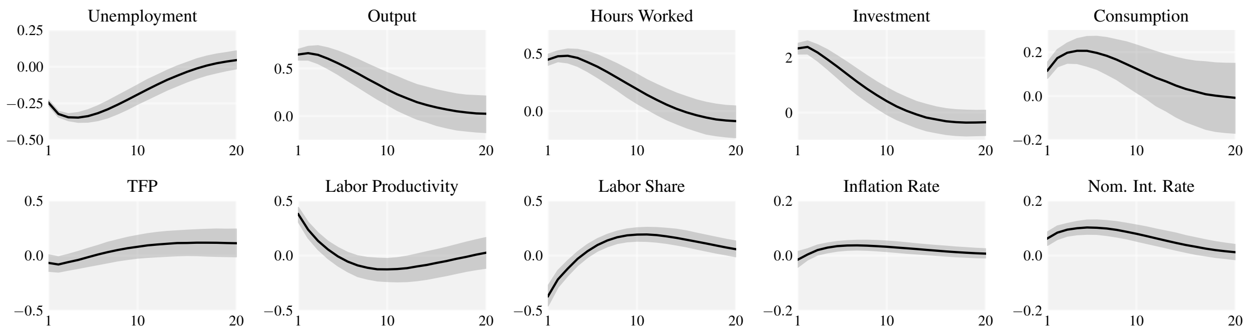
Table 1 adds more information about the identified shock by reporting its contribution to the volatility of all the variables over two frequency bands: the one used to construct it, which corresponds to the range between 6 and 32 quarters and is referred to as "Short Run" in the table; and a different band, which is referred to as "Long Run" and corresponds to the range between 80 quarters and ∞. This helps assess whether the identified shock can indeed account for the bulk of the business-cycle fluctuations in the key macroeconomic quantities, as well as how large its footprint is on inflation or the long run.[8]

What are the main properties of the identified shock?

First, over the business-cycle frequencies, it explains about 75% of the volatility in unemployment, 60% of that in investment and output, and 50% of that in hours. It also gives rise to a realistic business cycle, with all these variables and consumption moving in tandem. These properties together with those reported in the sequel justify labeling the identified shock as the "main business cycle shock."

[8]Figure 12 in Online Appendix D contains similar information as Table 1, but applied to the time domain: it reports the contributions of the identified shock to the forecast error variances (FEV) of the variables at different horizons.

Figure 1: Impulse Response Functions to the MBC Shock



Note: Impulse Response Functions of all the variables in our VAR to the identified MBC shock. Horizontal axis: time horizon in quarters. Shaded area : 68% Highest Posterior Density Interval (HPDI henceforth).

Table 1: Variance Contributions

	u	Y	h	I	C
Short Run (6-32 quarters)	73.71	58.51	47.72	62.09	20.38
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]
Long Run (80-∞ quarters)	20.83	4.64	5.45	5.16	4.13
	[8.37,38.94]	[0.52,15.85]	[1.25,15.40]	[0.79,16.81]	[0.38,14.93]
	TFP	Y/h	wh/Y	π	R
Short Run (6-32 quarters)	5.86	23.91	27.02	6.96	22.27
	[2.44,10.96]	[17.27,31.22]	[18.39,35.93]	[3.24,12.28]	[14.22,30.97]
Long Run (80-∞ quarters)	4.09	3.88	3.12	5.77	9.12
	[0.41,14.48]	[0.37,14.19]	[0.78,10.16]	[1.70,13.54]	[2.68,20.00]

Note: Variance contributions of the MBC shock at two frequency bands. The first row (Short Run) corresponds to the range between 6 and 32 quarters, the second row (Long Run) to the range between 80 quarters and ∞. The shock is constructed by targeting unemployment over the 6-32 range. The notation used for the variables is the same as that introduced Section 2. 68% HPDI into brackets.

Second, the identified shock contains little statistical information about the business-cycle variation in either TFP or labor productivity. This is *prima facia* inconsistent, not only with the baseline RBC model, but also with a class of models that let financial or other shocks trigger business cycles only, or primarily, by causing endogenous movements in productivity. We expand on this point in Section 3.3. Also, the mild and short-lived, procyclical response of labor productivity could reflect the impact of the latter on capacity utilization; this hypothesis is corroborated by the evidence in Online Appendix G.2.

Third, the contribution of the shock to economic activity peaks within a year of its occurrence, fades out before long, and leaves a negligible footprint on the long run. This finding extends and reinforces the message of Blanchard and Quah (1989): what drives the business cycle appears to be distinct from what drives productivity and output in the longer term. This point is further corroborated later.

Fourth, the shock triggers a small, almost negligible, and delayed movement in inflation. This precludes the interpretation of the identified shock as an inflationary demand shock of the textbook variety, but allows its interpretation as either a demand shock of the DSGE type, where the use of sufficiently flat wage and price Philips curves guarantee that demand shocks can generate sizable departures from flexible-price outcomes without commensurate inflationary pressures, or a demand shock operating outside the realm of nominal rigidities and Philips curves, as in the models cited in footnote 3. We revisit this point in Sections 3.4 and 6.

Fifth, the shock triggers a strong, procyclical movement in the nominal interest rate. And because inflation hardly moves, this translates to a strong, procyclical movement in the real interest rate. At face value, this seems consistent with a monetary policy that raises the nominal interest in response to the boom triggered by the identified shock, stabilizes inflation, and perhaps even closes the gap from flexible-price outcome (or, equivalently, tracks the natural rate of interest). This scenario is ruled out by the prevailing New Keynesian paradigm, because a gap from flexible-price outcomes is needed in order to accommodate demand-driven business cycles. But there is no way to verify or reject this assumption on purely empirical grounds, because the natural rate of interest and the flexible-price outcomes are not directly observable (and not even defined outside specific models).

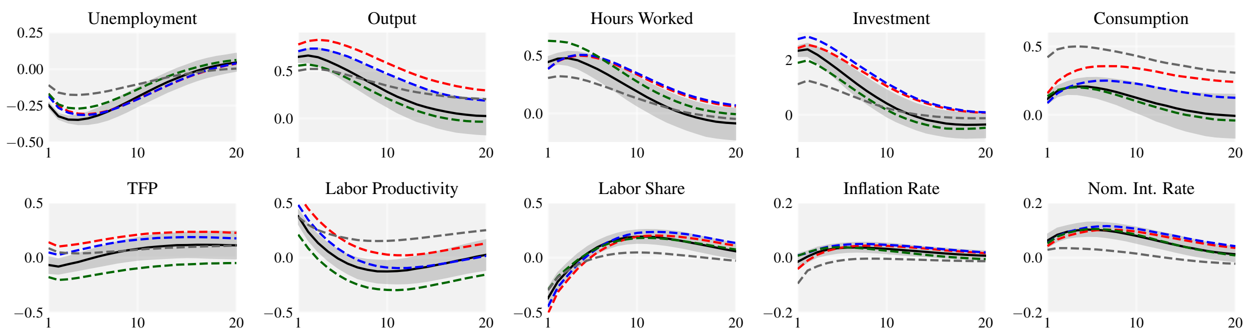
Finally, the shock triggers a countercyclical response in the labor share for the first few quarters, which is reversed later on. Relatedly, when looking at the response of the real wage, as inferred by the difference between the response of the labor share and that of labor productivity, we see that the real wage remains relatively flat in response to the identified shock. This is consistent with the well-known, unconditional fact that real wages display very weak procyclicality, which is typically interpreted as being due to some form of real-wage rigidity.

3.2 The Main Business Cycle Shock: Targeting Other Quantities

Figure 2 compares the IRFs of the shock that targets the business-cycle volatility of the unemployment rate (black line) to the IRFs of the shocks that are identified by targeting the business-cycle volatility of a some other key macroeconomic quantities: GDP (red line), hours (green line), investment (blue line), and consumption (gray line).

As is evident from the figure, these shocks are nearly indistinguishable: targeting any one of the aforementioned variables seems to give rise to the same dynamic comovement properties. This explains the rationale of interpreting these reduced-form shocks as interchangeable facets of the empirical footprint of the same propagation mechanism, or of what we have called the MBC shock.[9]

Figure 2: The Various Facets of the MBC Shock, IRFs



u shock; Y shock; I shock; h shock; C shock; Shaded area: 68% HPDI.

Table 2 paints a complementary picture in terms of the variance contributions: the shock that targets *any* one of unemployment, GDP, hours and investment explains the bulk of the business-cycle volatility in all of these variables. The following caveat applies to consumption: the shock that targets consumption explains less than one quarter of the fluctuations in unemployment, hours, or investment; and symmetrically, the other shocks that make up our MBC template account for less than one quarter of the fluctuations in consumption.[10] Nonetheless, the consumption shock conforms quite closely to the other shocks when it comes to the IRFs it induces, as well as in terms of the disconnect from TFP and inflation. That is, it shares roughly the same propagation mechanism.

Finally, the interchangeability property extends from the IRFs to the times series produced by the different facets of the MBC shock. This is shown in Table 3. The table reports, for any of the variables of

[9] Recall that, for our purposes, different shocks that are observationally equivalent in terms of IRFs are essentially one and the same shocks. This perspective is consistent with standard practice in both the SVAR and the DSGE literatures: as echoed in the quote from Cochrane cited in footnote 2, shocks are visible—and hence distinguishable—only through the dynamic comovement patterns they induce in the variables of interest.

[10] Recall that our measure of consumption excludes spending on durables, which is instead included in investment.

Table 2: The Various Facets of the MBC Shock, Variance Contributions

Targeted Variable	u	Y	h	I	C
Unemployment	73.71	58.51	47.72	62.09	20.38
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]
Output	56.24	80.13	44.73	67.13	33.03
	[48.94,61.93]	[72.80,86.44]	[37.36,51.68]	[60.72,72.82]	[25.04,40.44]
Hours Worked	49.84	47.54	70.45	47.99	21.78
	[42.43,56.53]	[38.20,55.67]	[64.25,77.04]	[38.49,55.96]	[15.30,29.22]
Investment	59.03	66.60	45.20	80.29	19.01
	[51.73,64.55]	[60.40,72.21]	[37.93,51.98]	[72.82,86.97]	[12.27,27.34]
Consumption	19.19	31.59	20.15	17.10	68.30
	[12.12,27.73]	[21.81,40.90]	[13.60,27.68]	[9.96,25.94]	[60.61,75.53]
Targeted Variable	TFP	Y/h	wh/Y	π	R
Unemployment	5.86	23.91	27.02	6.96	22.27
	[2.44,10.96]	[17.27,31.22]	[18.39,35.93]	[3.24,12.28]	[14.22,30.97]
Output	4.24	41.31	40.20	10.47	16.89
	[1.76, 8.32]	[35.29,47.43]	[32.75,47.40]	[5.97,16.75]	[11.00,26.08]
Hours Worked	11.62	22.61	19.47	7.23	22.38
	[6.14,18.14]	[15.58,29.66]	[11.73,29.24]	[3.32,13.31]	[15.09,31.87]
Investment	3.81	33.74	36.44	7.69	21.51
	[1.38, 7.83]	[27.72,40.30]	[29.21,44.21]	[3.65,12.96]	[13.91,30.28]
Consumption	1.57	12.93	10.31	9.93	4.50
	[0.59, 3.57]	[7.40,20.54]	[5.08,17.88]	[4.70,17.05]	[1.38,10.63]

Note: The rows correspond to different targets in the construction of the shock. The columns give the contributions of the constructed shock to the business-cycle volatility of the variables. In this and in all following tables, square brackets contain the 68% HPDI.

Table 3: Correlations of Conditional Times Series

	Y shock	I shock	C shock	h shock
Unemployment	0.973	0.982	0.931	0.941
Output	0.997	0.997	0.991	0.992
Investment	0.990	0.996	0.938	0.989
Consumption	0.987	0.983	0.739	0.964
Hours Worked	0.973	0.982	0.931	0.941

Note: Each row reports the correlation between each bandpass-filtered variable as predicted by the unemployment shock and that predicted by the other facets of the MBC shock.

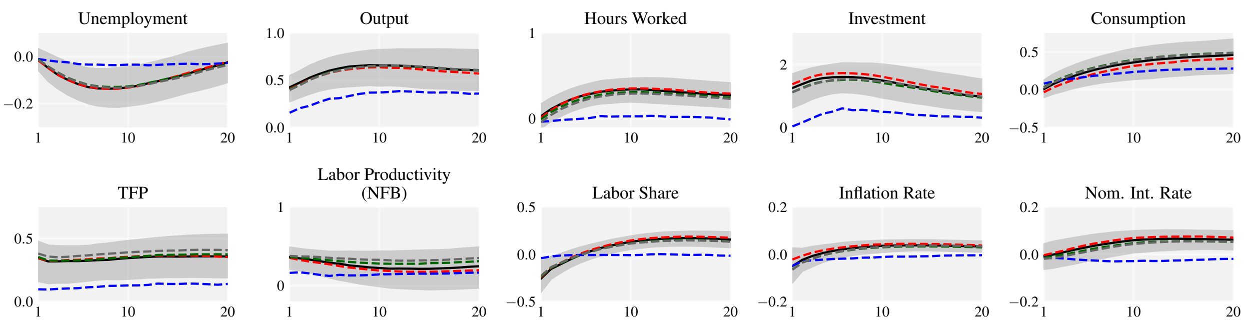
interest, the correlations between the times series of that variable produced by the unemployment shock and that produced by any of its sister shocks. The nearly perfect correlations seen in this table mean that that recovered shocks are essentially the same, not only in terms of IRFs, but also in terms of realizations, as manifested in the times series they produce for the main variables of interest.[11]

3.3 The Long Run and the Short Run

In the preceding analysis we recovered a MBC shock by targeting the business cycle frequencies. We now document the existence of an analogous object for the long run frequencies. We also discuss the implications of our results for theories that link the business cycle to technology and news shocks.

Consider the shocks that target GDP, investment, consumption, TFP, or labor productivity at the frequencies corresponding to 80-∞ quarters. Figure 3 and Table 4 show that these shocks are nearly indistinguishable in terms of IRFs and variance contributions. Hence, one may advance the concept of the "main long-run shock" in a manner analogous to that of the MBC.[12]

Figure 3: Long-Run Shocks



Y shock; I shock; C shock; Y/h shock; TFP shock; Shaded area: 68% HPDI.

This finding also motivates us to repeat our exercises using a VECM in which the aforementioned quantities share a common stochastic trend, while the remaining variables are stationary. The use of

[11]Let $X \in \{u, Y, C, I, h\}$ denote any one of the variables of interest. Next, let X_s denote the bandpass-filtered time series of the predicted value of that variable produced by the shock that targets the variable $s \in \{u, Y, C, I, h\}$ (where s may or may not coincide with X). We are using the band pass filter suggested by Christiano and Fitzgerald (2003). The typical cell in Table 3 reports, for a variable X (across rows) and a shock $s \neq u$ (across columns), the correlation of X_s and X_u. This summarizes the information seen in Figure 9 in Appendix B, which depicts the full scatterplots of the series X_s against the series X_u, for all X and s. The similarity is also present in terms of the *innovations* that correspond to the different shocks. But these innovations are not meaningful per se, nor are the corresponding column vectors of the matrix Q. Rather, what matters is how these innovations propagate over time and across variables, which is what the IRFs seen in Figure 2 reveal, or how they manifest themselves in terms of the predicted time series X_s, which explains the focus of Table 3 and Figure 9.

[12]We have verified that the shocks considered here are nearly identical to those identified by targeting the frequency exactly at ∞, which amounts to imposing a set of long-run restrictions as in Blanchard and Quah (1989) and Galí (1999). A similar picture also emerges from inspection of the first principal component over these long term data; see Table 18 in Appendix F.

Table 4: Long-Run Shocks, Contributions at Long-Run Frequencies (80-∞ q)

Targeted Variable	Y	I	C	TFP	Y/h
Output	99.59	95.94	99.47	95.66	96.92
	[98.53,99.92]	[89.26,98.93]	[98.33,99.86]	[88.38,98.87]	[90.68,99.13]
Investment	96.88	97.83	96.41	91.62	91.75
	[88.35,99.39]	[93.39,99.39]	[87.05,99.31]	[74.88,97.83]	[72.74,97.94]
Consumption	99.34	95.63	99.53	95.39	96.69
	[97.57,99.85]	[87.91,98.81]	[98.23,99.90]	[87.38,98.81]	[90.51,99.12]
TFP	97.39	92.55	97.40	98.43	98.43
	[88.33,99.48]	[76.41,98.11]	[88.33,99.49]	[94.49,99.70]	[93.92,99.67]
Labor Productivity	98.30	93.23	98.55	97.60	98.97
	[91.73,99.60]	[77.39,98.28]	[92.92,99.66]	[91.37,99.50]	[95.10,99.84]

Table 5: VECM, Long-Run TFP Shock, Contributions at Business-Cycle Frequencies

u	Y	h	I	C
9.63	24.78	11.01	17.56	15.58
[3.46,18.43]	[11.41,40.32]	[4.99,19.60]	[7.31,29.53]	[5.71,27.20]
TFP	Y/h	wh/Y	π	R
22.01	21.89	10.19	12.59	7.26
[5.95,42.17]	[10.96,35.27]	[2.75,21.70]	[4.64,28.59]	[2.52,16.84]

such a VECM instead of our baseline VAR is recommended if the analyst has a strong prior that the aforementioned quantities are cointegrated—a prior that is not only imposed in standard models but also corroborated by the evidence presented above as well as by familiar cointegration tests. For robustness, we also consider a variant VECM in which we add a second stochastic trend that drives inflation and the nominal interest rate. This helps capture the familiar indeterminacy of the long-run values of these variables in theoretical models and their high persistence in the actual data.

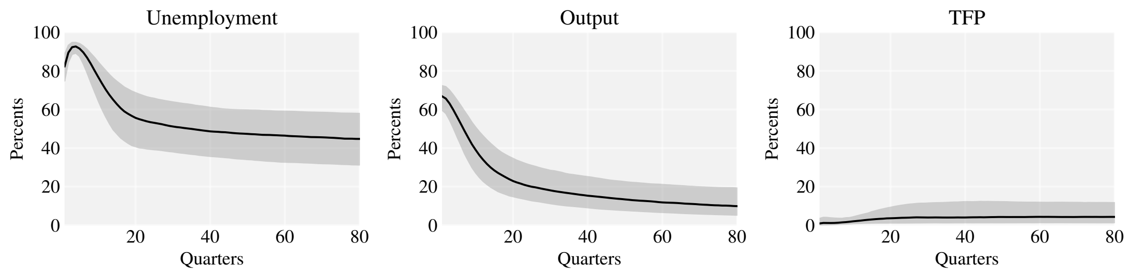
These VECMs produce essentially the same empirical regularities as those presented above. An example of this robustness is provided in Table 5. This table reports the contribution of the main long run shock, represented by the shock that targets TFP over the 80-∞ range, to the volatilities of all the variables over the 6-32 range. The emerging picture is essentially the mirror image of that contained in the second row of Table 1. There, we reported that the MBC shock has a small contribution to the long run. Here, we see that the shock that accounts for the long run has a small footprint on the business cycle.

The disconnect between the short and the long run can also be seen in Figure 4, which shows the contribution of the MBC shock to the forecast error variance (FEV) of unemployment, output and TFP at different time horizons.[13] The MBC shock explains more than 60% of unemployment and output move-

[13]The MBC shock is still identified in the frequency domain. The alternative of identifying same picture emerges when the

ments during the first two years, but less than 7% of the TFP movements at *any* horizon; and conversely, the main long run shock explains nearly all the long-run variation in investment and TFP, but less than 10% of the unemployment and investment movements over the first two year.[14]

Figure 4: FEVs of Unemployment, GDP and TFP to the MBC shock



Shaded area: 68% HPDI

How do these findings compare to related ones in the existing literature?

First, consider Blanchard and Quah (1989). They seek to represent the data in terms of two shocks, a "supply shock" and a "demand shock." To this goal, they run a VAR on two variables, GDP and unemployment; identify the supply shock as the shock that accounts for GDP movements in the very long run (at ∞) and the demand shock as the residual shock; and document that the supply shock account for about 50% of the business-cycle volatility in GDP and a bit more of that in unemployment. The additional information contained in our larger VAR reduces the contribution of the supply shock to about 25% for GDP and about 10% for unemployment.

Second, consider Uhlig (2003). This work, too, pursues a two-shock representation of the data. The main difference from Blanchard and Quah (1989) is that it uses a different identification scheme: it identifies the two shocks that *jointly* maximize the forecast error variance (FEV) in real GNP for horizons between 0 and 5 years. Uhlig offers a tentative interpretation of one shock as being a productivity shock of the RBC type and the other as a cost-push shock of the New Keynesian type. This interpretation finds little support in our anatomy, especially due to our finding of a disconnect between our main business-cycle shock and TFP at all horizons.[15] Furthermore, as explained in Section 4.2, once we move from the frequency domain to the time domain, the business cycle is best captured by targeting the FEVs of

MBC is identified in the time domain, provided that one uses "right" mapping between the two domains. See Appendix E.

[14]It is worth noting that the disconnect between the short and the long run extends from neutral technology, as measured by TFP, to investment-specific technology, as measured by the relative price of investment; see Appendix G.2.

[15]We emphasize that the interpretation offered in Uhlig (2003) was tentative as that paper was not completed. Also note that the approach adopted in that paper allows for the identification of the two shocks *together* but does not separate one shock from the other, so the aforementioned interpretation relied on particular orthogonalizations. Finally, because the VAR considered in that paper did not contain TFP, the disconnect documented here could not have been detected.

unemployment and GDP at 1 year, as opposed to longer horizons.

Third, consider Galí (1999) and Francis et al. (2014). Our long-run TFP shock is essentially the same as the technology shock identified in those papers. Tables 4 and 5 confirm their finding that this shock has a small contribution to the business cycle. This property extends to the robustness exercises reviewed in Section 4.3. It also connects to the point made next.

Finally, consider Beaudry and Portier (2006). The first part of that paper uses a two-variable VAR with TFP and the SP500 index to identify a shock that has zero impact effect on TFP but accounts accounts for the bulk of both the short-run movements in stock prices and the long-run movements in TFP. This shock is interpreted as "news" about future TFP. The second part proceeds to argue, using three- to five-variable VARs and additional identifying restrictions, that TFP news shocks account for about 50% of the short-run volatility in hours and total private spending, about 80% of that in consumption, and about 80% the long-run movements in private spending. In short, TFP news emerges as the main driver of *both* the business cycle and the long run.

This picture is hard to reconcile with our results, as well as with those of Galí (1999) and Francis et al. (2014). If TFP news was the main driver of *both* the business cycle and the long run, one would expect to see a strong connection between the two. But as seen in Table 5, the main long-run shock identified here accounts for only 10% of the short-run volatility in unemployment and hours and 17% of that in investment. A similar disconnect is found in Galí (1999) and Francis et al. (2014).

Perhaps most tellingly, Figure 4 above shows that the MBC shock accounts for nearly zero of the FEV of TFP at *any* horizon. That is, the MBC shock itself contains no news about future TFP.[16]

We believe that, while TFP news may be a non-trivial contributor to macroeconomic fluctuations, the numbers reported by Beaudry and Portier (2006) exaggerate its importance due to the use of smaller VARs and different identifying assumptions. We elaborate on these points in Section 5 and Appendix C. There, we use a semi-structural exercise, based on our anatomy of the data, to shed new light on the business-cycle effects of technology and news shocks. Our explorations suggest that the contribution of news shocks to unemployment fluctuations is about 10%, which is much more modest than that suggested by Beaudry and Portier (2006) and closer to that reported in Barsky and Sims (2011).

A similar challenge applies to Lorenzoni (2009). That paper emphasizes the role of noise in the signals of future TFP, but maintains the core hypothesis that the business cycle is driven by shifts in the rational

[16]These findings are not due to the absence of Stock Prices in the VARs. As can be seen in row 9 of Table 8, which appears in the sequel and reports results from various robustness exercises, the inclusion of Stock Prices is inconsequential for the properties of the MBC shock as well as for those of the short and long run TFP shocks.

expectations of the long run, which is hard to reconcile with our findings.[17]

What is left open is the possibility that that the identified MBC shock reflects either *irrational* beliefs about the long run, or news about the *short run.* A formalization of the latter kind of news is found in our companion paper (Angeletos, Collard, and Dellas, 2018), to which we return in Section 6.

3.4 Inflation and the Business Cycle

We now turn attention to the nexus of real economic activity and inflation. Seen through the lens of our method, the link is weak. First, as shown in the first row of Table 6 (which repeats a portion of the first row of Table 1), the identified MBC shock accounts for only 7% of the business-cycle variation in inflation, which is as low as the corresponding number for TFP. Second, the shock that targets inflation explains 83% of the business-cycle volatility in inflation and only 4 to 8% of that in unemployment, output, and investment. Finally, the shock that targets inflation explains only 2% of the labor share, a commonly used proxy of the real marginal cost, or the driving force of inflation according to the New Keynesian Philips Curve (Galí and Gertler, 1999); and symmetrically, the shock that targets the labor share explains 86% of the labor share itself but only 4% of inflation.

Table 6: Inflation and the Business Cycle

Targeted Variable	u	Y	π	Wh/Y
Unemployment	73.71	58.51	6.96	27.02
	[66.80,79.94]	[50.65,65.07]	[3.24,12.28]	[18.39,35.93]
Inflation	4.24	7.88	83.03	1.96
	[1.62, 8.20]	[3.77,12.87]	[76.11,88.46]	[0.66, 4.60]
Labor Share	26.01	35.33	4.03	85.59
	[18.13,33.99]	[27.88,43.68]	[1.45, 7.94]	[80.04,90.02]

What is the lesson for theory? Because of its transitory nature and its disconnect from TFP, it is tempting to interpret the MBC shock in the data as a demand shock in the New Keynesian model. However, in that model demand shocks generate business cycles only by inducing positive output gaps from flexible-price outcomes. Furthermore, because replicating flexible-price outcomes is equivalent to stabilizing inflation, such gaps are the main "fundamental" driving inflation. In particular, insofar as business cycles are predominantly demand-driven, the textbook New Keynesian model imposes that inflation is the best predictor of future output gaps, or real marginal costs, similarly to how the textbook asset-pricing model imposes that the asset prices is the best predictor of future earnings. From this perspective, Ta-

[17] By shifting the focus from the distinct *theoretical* formulation of TFP news and noise shocks to their shared *empirical* footprint in terms of VAR representations of the data, we echo the related point made in Chahrour and Jurado (2018).

ble 6 suggests that the failure of the two models are comparable: the link between inflation and real economic activity is no better than the link between asset prices and earnings.[18]

Another challenge emerges from contrasting the magnitude of the actual inflation response to the identified MBC shock to that predicted the textbook version of the New Keynesian model under the interpretation of this shock as an aggregate demand shock in the theory: as illustrated in Figure 24 in Online Appendix I.1, the predicted response is over ten times larger than the observed one.

These challenges are familiar, albeit through other lenses.[19] The DSGE literature has sought to address them by making the Phillips curve much flatter than, not only its textbook version, but also that implied by menu-cost models calibrated to micro-economic evidence; and by letting large enough markup shocks engineer the requisite variation in inflation despite the assumed large degree of nominal rigidity.

The empirical foundations of these and other features that help improve the empirical fit of DSGE models remains a contested issue, certainly beyond the scope of this paper. We also do not mean to question the empirical relevance of nominal rigidities or the non-neutrality of monetary policy. But we do wish to raise the possibility that the MBC shock in the data represents an aggregate demand shock of a different kind that that presently formalized in the New Keynesian framework, namely one that operates *inside* its flexible-price core rather than outside it. This echoes the common message of Angeletos and La'O (2013), Beaudry and Portier (2014), and the literature cited in footnote 3.

4 Robustness

In this section we first discuss the relation between our approach and two alternatives: principal component analysis; and identification in the time domain. We next report results from an extensive battery of robustness exercises we have conducted.

4.1 The MBC Shock and Principal Component Analysis

The finding that there is a single force that drives multiple measures of economic activity naturally invites a comparison to principal component analysis (PCA). Is our MBC shock similar to the first principal component of the data over business cycle frequencies? And if yes, are there any reasons to favor employing our method over PCA in pursuing an anatomy of the business cycle?[20]

[18] As one would expect, the link improves somewhat if we focus on the pre-Volker period. See row 7 of Table 8 in Section 4.3.

[19] For instance, the weak comovement of inflation and real economic activity is also evident in the unconditional moments, although it is less pronounced than that seen in Table 6. See also the survey by Mavroeidis, Plagborg-Møller, and Stock (2014) on the large empirical literature on the various incarnations of the Phillips curve.

[20] We thank an anonymous referee for suggesting the exploration of these questions.

To address the first question, we perform PCA in the frequency domain. For each variable $X_j \in \{u, Y, h, I, ...\}$, we construct the bandpass-filtered variable X_j^{BC} that isolates its business cycle frequencies (6-32 quarters). We then use the covariance matrix of all the filtered variables to construct the first principal component, denoted by $PC1^{\mathrm{BC}}$. We finally project each X_j^{BC} on $PC1^{\mathrm{BC}}$ and compute the R-square of the projection. This gives the percentage of the business-cycle volatility in variable j accounted for by the principal component.[21]

Four different versions of this exercise are carried out. In the first version, X^{BC} is derived by applying the bandpass filter directly on the raw data, variable by variable. In the second version, we first run a VAR on all the variables jointly, use it to estimate the cross-spectrum of the data, and then construct the band passed variables X_j^{BC}. Hence, the bandpass filter is the ideal one in the latter case, whereas it is only an approximate one in the former.

In the third and fourth version, the filtered variables are normalized by their respective standard deviations before extracting the first principal component. Such a normalization is often employed in the PCA literature in order to cope with scaling issues and/or to focus on the co-movements in the data. But it also reduces the role played by the more volatile variables (e.g., investment), which may or may not be desirable depending on the context. As we do not have a strong prior on how to properly weight the variables, we carry the exercise on both normalized and non-normalized data.

The results are reported in Table 7. In all cases, the first principal component accounts for the bulk of the business-cycle volatility in unemployment, hours, output, and investment but only a small fraction of the business-cycle volatility in either TFP or inflation.

Table 7: The First Principal Component, Business Cycle Frequencies

	u	Y	h	I	C	TFP	Y/h	wh/Y	π	R
Raw Data	75.33	92.26	81.24	99.80	60.19	6.10	17.73	3.02	2.33	12.27
VAR-Based	63.31	87.33	62.47	99.72	26.67	1.22	29.19	14.16	0.68	8.10
Normalized Raw	91.50	86.76	91.26	80.59	76.75	17.32	2.59	0.33	19.22	38.21
Normalized VAR	82.87	93.86	78.12	82.59	54.86	1.81	19.36	5.28	2.09	19.63

This is reassuring: the picture obtained here is similar to that obtained in Table 2 about the various facets of the MBC shock. As shown in Online Appendix F, a similarly reassuring connection holds between the main long-run shock obtained by our method in the next section and the principal component obtained by applying PCA to the long-run components of the data.

[21] Recall that the first principal component is constructed by taking the eigenvector corresponding to the largest eigenvalue of the covariance matrix. It is thus designed to account for as much as possible of the volatility and the co-movement of all the (filtered) variables at once.

However, there are three key pieces of information that our approach produces but PCA does not. First, PCA is not useful for addressing the question of whether the forces that drive the business cycle and long run are related, because the aforementioned two principal components are orthogonal to each other *by construction*. Second, PCA does not contain information about how the variables respond on impact and over time to a shock; that is, PCA does not accommodate the construction of IRFs, which are of paramount importance for our purposes. And third, by targeting each time an individual variable but also systematically varying the possible targets, our method avoids the difficulties associated with having to choose the "best" weights in PCA and, more importantly, helps reveal patterns that may prove useful in the validation of existing models or in the construction of new ones.

A version of Dynamic Factor Analysis, appropriately adapted to the frequency domain, could address the first two caveats of PCA and offer a more useful complement to our approach. But it would not immediately accommodate the third point mentioned above, which plays a big role in our approach: the information extracted by taking multiple cuts of the data.

Consider, in particular, the interchangeability pattern documented in Figure 2. This finding offers, not only hope for parsimonious models that aspire to account for the majority of business cycles with a single shock/mechanism, but also a test for models that employ a multitude of shocks/mechanisms. This will become clear in Section 6.

4.2 MBC in the Frequency Domain vs the Time Domain

A long rooted convention in empirical macroeconomics identifies the business cycle with the fluctuations occurring in the 6-32 quarters range in the frequency domain (FD).[22] In line with this tradition, our MBC shock is constructed by identifying the shock that accounts the most of the volatility of unemployment and other key macro quantities in that range.

But suppose one wished to identify business cycles in the time domain (TD). Which horizon(s) should one target?

At first glance, one may think that targeting volatility over the 6-32 quarters band in the FD is equivalent to targeting volatility over the 6-32 quarters horizon range in the TD. But this is wrong: such a relation does not hold for arbitrary DGPs (or arbitrary models), nor does it hold in the actual data.

We offer a comprehensive treatment of this issue in Appendix E by undertaking two exercises, one theoretical and one empirical.

[22] This convention stretches back at least to Mitchell. More recently, when researchers document business-cycle moments whether in the data or in a model, they almost invariably use either the BP filter at the 6-32 quarters band or the HP filter, which is closely related (e.g. Stock and Watson, 1999).

In the first exercise, we set up a 3×3 model (three variables, three shocks). Although the model is deliberately abstract, its variables can loosely be interpreted as unemployment, output and inflation. Its main purpose is to serve as a controlled laboratory environment, in which we can work out the properties of alternative mappings between the FD and the TD.

Within this controlled environment, we establish two properties of the MBC shock identified via our method, that is, by targeting the volatility of the first two variables over the 6-32 quarters in the FD:

1. This shock is notably different from the shock that targets 6-32 quarters in the TD.
2. This shock is nearly identical to the one that targets 4 quarters in the TD.

This serves both as a proof of concept that the mapping between the FD and the TD is non-trivial in general, and as an illustration of the kind of model that best fits the data.

The second exercise completes the picture by showing that the two properties mentioned above indeed characterize the data. A hint that the second property is true in the data was already present in Figures 1 and 4, which showed that footprint of our MBC shock in the TD, in terms of both IRFs and FEVs, was peaking within a year or so.

These findings complement the picture painted in the rest of our paper. They also illustrate why TD-based identification strategies that maximize the FEV contribution of a shock to unemployment or output at longer horizons could fail to capture business cycles.

4.3 Alternative Specifications

We now turn to the robustness of our main results in a variety of dimensions (sample periods, set of variables, assumptions about stationarity, numbers of lags). The main exercises are described below, a few additional ones are delegated to the Appendix.

Table 8 describes the variance contribution of the MBC shock over business cycle and longer term frequencies, respectively, and across many alternative specifications (different samples, statistical models estimated, set of variables, numbers of lags). As in Table 1, we use the shock that targets unemployment as the measure of the MBC shock. Appendix G reports similar tables for the shocks that target GDP, hours, etc... The first row in Tables 8 corresponds to our baseline specification, that is, it repeats the information from Table 1. The remaining rows correspond to ten alternative specifications.

Row 2 corresponds to a VAR with four lags instead of two; the results with six or eight lags are almost the same and are thus omitted. Rows 3 and 4 correspond to two VECMs: the first allows for a single unit root that drives the real quantities, while the second allows inflation and the nominal interest rate to be driven by the first, “real” root as well as by a second, “nominal” root. Row 5 extends the sample backwards to 1948, by replacing the Federal Reserve Rate with the 1-month T-bill rate. Row 6 constrains the sample to 1960-2007, leaving out the Great Recession and the ZLB; this is also the period used in the estimation and validation of the two DSGE models considered in the next section. Rows 7 and 8 split the sample to two sub-samples, pre- and post-Volcker. Row 9 adds the following three variables to the VAR: the SP500 index, the relative price of investment, and capital utilization. Row 10 adds the credit spread, a common measure of the severity of financial frictions. Finally, row 11 considers a version where consumption and investment are deflated by their respective, chained-type price indices rather than the GDP deflator, as a way to take relative-price effects into account.[23]

The results speak for themselves. As we move across specifications (rows), the contribution of the identified shock to the variance of the key macroeconomic quantities remains almost unchanged.[24] Similar results obtain in additional robustness exercises which we have undertaken but omit here for the sake of saving space.[25]

More importantly, the same robustness is present when considering the IRFs. We illustrate this in Figure 5 for the shock that targets unemployment for a select subset of the eleven specifications under consideration.[26] This is re-assuring as the properties of the IRFs, and in particular the interchangeability of the various facets of the MBC shock, represent the key criterion for judging the empirical plausibility of a model's propagation mechanism.[27]

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[23]Given that consumption is the sum of non durables and services, and investment is the sum of gross private domestic investment and durables, some care must be take to build the corresponding chained type price indices. The construction of the indices is detailed in Appendix G.5.

[24]The only sensitivities worth mentioning are the following. First, the VECMs raise slightly the long-run footprint of the MBC shock and more noticeably its short-run co-movement with consumption. And second, the pre-Volcker sample features a smaller disconnect between real economic activity and inflation than the post-Volcker one. These findings are hardly surprising and, in any case, do not change the main picture.

[25]For instance, we have verified that the properties of the MBC shock remain largely the same if we drop any one of the variables in our baseline VAR, or if we add labor market indicators such a vacancies. The results become sensitive only when the size of the VAR becomes very small. See Appendix C for an illustration. This is not surprising given the well-known fragility of small VARs. To the contrary, this fact along with the already reported robustness to the addition of stock prices and other variables suggests that our baseline VAR has the "right" size in order to reveal robust properties.

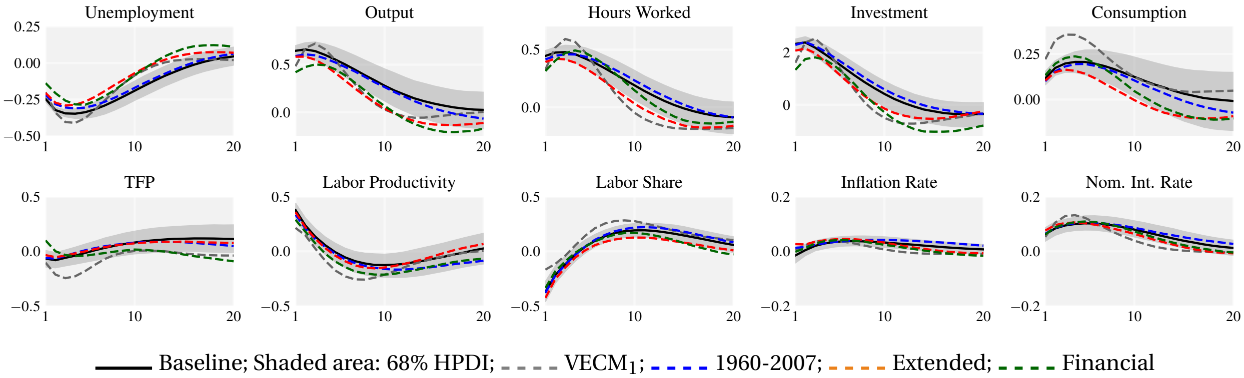
[26]The remaining specifications are also similar. They are omitted only because they would have over-crowded the figure.

[27]As can been seen by comparing the baseline and the 1960-2007 cases in Figure 5, the interchangeability property and the profile of the MBC shock are not sensitive to the inclusion or exclusion of the ZLB period. This fact may seem puzzling when viewed through the lenses of a model in which the ZLB constraint is binding and dramatically changes the propagation of the main driver(s) of the business cycle. But if this constraint is largely bypassed by the effective use of other policy tools, the main propagation mechanism seen in the data need not change as one moves between ZLB and non-ZLB samples; see Debortoli, Galí, and Gambetti (2019) for corroborating evidence. Yet another possibility is that the ZLB constraint matters for the amplitude of the business cycle but not for the propagation dynamics.

Table 8: Robustness, Variance Contributions

	Short Run Contribution							Long Run Contribution	
	u	Y	h	I	C	TFP	π	Y	TFP
[1] Benchmark	73.71	58.51	47.72	62.09	20.38	5.86	6.96	4.64	4.09
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]	[2.44,10.96]	[3.24,12.28]	[0.52,15.85]	[0.41,14.48]
[2] 4 lags	74.49	58.23	49.16	62.42	21.20	6.28	6.91	4.39	3.66
	[67.98,80.77]	[50.51,65.05]	[42.24,56.10]	[55.15,69.04]	[14.13,28.78]	[2.82,11.74]	[3.23,12.15]	[0.61,14.67]	[0.41,13.53]
[3] VECM(1)	62.43	50.27	48.81	53.39	34.88	18.13	10.46	14.07	14.07
	[56.47,68.44]	[43.46,57.44]	[42.14,55.91]	[47.05,60.01]	[26.27,44.47]	[9.03,29.45]	[4.39,20.13]	[2.53,29.11]	[2.53,29.11]
[4] VECM(2)	64.85	54.99	48.82	53.78	44.93	12.17	11.29	16.70	16.70
	[57.60,71.25]	[46.53,62.59]	[42.52,55.66]	[46.37,60.86]	[33.73,55.68]	[6.00,19.88]	[5.09,19.32]	[3.31,37.32]	[3.31,37.32]
[5] 1948-2017	78.98	65.32	49.61	63.76	19.52	6.14	5.16	7.44	7.20
	[72.86,84.10]	[59.25,71.33]	[43.55,55.83]	[57.87,70.19]	[13.70,26.91]	[2.51,11.05]	[2.28,10.00]	[1.22,19.37]	[1.12,19.01]
[6] 1960-2007	68.15	59.93	55.99	65.02	20.67	6.02	10.70	4.17	4.11
	[61.82,73.98]	[48.14,68.85]	[47.10,63.10]	[55.39,72.59]	[13.52,31.01]	[2.24,13.76]	[5.49,18.89]	[0.52,16.00]	[0.73,14.05]
[7] pre-Volcker	74.23	56.75	43.21	61.50	23.43	6.82	17.45	8.15	7.31
	[64.05,82.35]	[45.87,66.62]	[32.38,53.49]	[51.63,70.37]	[13.58,35.24]	[2.45,15.11]	[9.39,28.74]	[1.21,26.52]	[0.96,25.64]
[8] post-Volcker	73.39	50.37	50.65	58.44	20.23	7.94	4.65	3.58	3.41
	[65.47,80.53]	[41.45,58.81]	[42.60,59.01]	[50.17,66.23]	[12.46,28.65]	[3.67,14.49]	[1.74,10.06]	[0.80,12.17]	[0.55,11.59]
[9] Extended	59.33	50.61	45.50	52.91	21.83	4.81	12.12	4.52	4.39
	[53.73,65.69]	[43.05,57.99]	[39.71,51.26]	[44.97,60.17]	[14.87,31.14]	[1.95,10.39]	[6.57,19.70]	[0.45,17.60]	[0.59,17.66]
[10] Financial	68.57	57.56	46.84	59.95	25.94	7.04	8.42	4.85	4.26
	[62.38,74.87]	[49.74,64.87]	[39.39,54.03]	[52.26,66.82]	[17.80,34.98]	[3.10,12.97]	[3.77,14.98]	[0.54,15.56]	[0.59,14.78]
[11] Chained-Type C&I	81.41	59.04	45.96	61.52	17.36	4.03	5.82	3.79	3.67
	[75.30,86.36]	[52.45,64.82]	[39.33,52.36]	[54.39,67.49]	[12.10,23.41]	[1.56, 7.51]	[2.62,10.41]	[0.49,14.58]	[0.54,13.27]

Figure 5: Robustness, IRFs



5 Interpretation

In this section, we first summarize what can be learned from the properties of our anatomy if one views them from a parsimonious, single-shock perspective. We then discuss the robustness of such lessons and the use of our anatomy outside the realm of single-shock models.

5.1 The Lesson for Parsimonious, Single-Shock Models

In the beginning of the Introduction, we asked: Is it possible to account for the bulk of the business cycle with a parsimonious, single-shock model? And if so, how should this shock look like? Our empirical findings provide the following answer.

Tentative lesson. *It is possible to account for the bulk of the business-cycle fluctuations in unemployment, hours, GDP, investment, and, to a somewhat lesser extent, consumption using a parsimonious, one-shock model. This shock must have the following key properties:*

- *it causes strong, positive, and transient comovements in the aforementioned quantities;*
- *it is an indicator of the short-run economic outlook and not of the medium- and long-run prospects;*
- *it is essentially orthogonal to both TFP and inflation at all horizons;*

As already discussed, these properties are hard to reconcile with the baseline RBC model, as well as with models that attribute the bulk of the business cycle to news about productivity and income in the medium to long run. They also speak against models in which financial, uncertainty, or other shocks matter primarily by triggering endogenous procyclical movements in aggregate TFP.[28] In contrast, the evidence seems consistent with a shock that triggers transitory movements in the labor wedge—but only insofar as these movements occur without commensurate movements in aggregate TFP and without opposite movements in the real wage. This rules out shocks to labor supply, as well as productivity shocks intermediated by labor-market frictions, but leaves room for other possibilities.[29] The evidence is also consistent with the Keynesian narrative that the bulk of the business cycle is due to shifts in aggregate demand—but only insofar as these shifts do not trigger significant movements in inflation. This, in turn, requires either a very flat Philips curve, as in state-of-the-art DSGE models, or demand shocks operating outside the realm of sticky prices and Philips curves, as Angeletos and La'O (2013), Beaudry and Portier (2014) and the additional literature cited in footnote 3 in the Introduction.

5.2 The Anatomy of Multi-Shock Models

So far, we have attempted to give structural meaning to the identified MBC shock through the lenses of models that aspire to explain the bulk of the observed business cycles with a single shock/propagation mechanism. This choice reflects, in part, a "philosophical" attitude. But this choice can be consequential for the interpretation of the MBC shock and more generally for the use of our anatomy. As suggested in the Introduction, the reason is that, in principle, any of the reduced-form objects contained in our anatomy may map into a un-interpretable combination of multiple theoretical shocks, none of which possesses the properties of the empirical object.

In this section, we use two examples to illustrate both this challenge and a resolution offered by our method. By design, our anatomy contains not only the reduced-form shock that targets unemployment over the business-cycle frequencies but also the other reduced-form shocks we have discussed in the previous section. This additional information comes into play when there is more than one shock in the model and holds the key for the effectiveness of our anatomy in multi-shock contexts. It turns out, at least within the set of semi-structural and fully-structural exercises consider in this and the next section, that this extra information suffices to pin down the nature of the main driving force of the business cycle, corroborating the main claim from the previous section, namely, that this force corresponds to a non-inflationary, demand shock.[30]

[28] Benhabib and Farmer (1994) and Bloom et al. (2018) are notable examples of such models: the former generates procyclical TFP movements out of animal spirits, the latter out of uncertainty shocks.

[29] For example, in Angeletos, Collard, and Dellas (2018) the requisite movements in the measured labor wedge are the byproduct of higher-order uncertainty about the short-term economic outlook; in Arellano, Bai, and Kehoe (2019) these movements are attributed to the interaction of financial frictions and firm-level uncertainty shocks; and in Golosov and Menzio (2015) they obtain from animal spirits in frictional labor markets.

[30] Needless to say, this particular conclusion need not extend to *arbitrary* multi-shock models, because any structural inter-

Our first pedagogical example revisits the disconnect between the MBC shock and inflation within the textbook AD-AS paradigm. Let the AD and AS equations be given by, respectively,

$$y_t = -\pi_t + v_t^s \qquad \text{and} \qquad \pi_t = y_t + v_t^s, \tag{2}$$

where y_t denotes output, π_t denotes inflation, and v_t^d and v_t^s are the structural shocks to aggregate demand and aggregate supply, respectively. Imposing equilibrium gives

$$y_t = \tfrac{1}{2}(v_t^d + v_t^s) \qquad \text{and} \qquad \pi_t = \tfrac{1}{2}(v_t^d - v_t^s).$$

Assume now that v_t^d and v_t^s follow independent AR(1) processes, with the same persistence and variance. This implies (i) that each structural shock drives 50% of the volatility of both output and inflation and (ii) that output and inflation are orthogonal to each other. As a result, our "output shock," which is here given by output itself, accounts for 100% of the fluctuations in output and 0% of those in inflation. This matches the MBC shock seen in the data, but rather than representing a single, dominant, non-inflationary, business-cycle shock, it is the sum of two distinct structural shocks, an inflationary and a dis-inflationary one.

Our second example demonstrates that a similar problem may plague the interpretation of the finding that the short and the long run factors are disconnected. Consider a model that contains two types of TFP shocks, namely, unanticipated and anticipated (news) shocks. Suppose further that each shock contributes 50% of the long-run volatility in TFP and 50% of the short-run volatility in unemployment. Finally, let the two shocks have symmetrically opposite effects on unemployment, one increasing it and the other decreasing it. The constructed "unemployment shock" then accounts for 100% of the short-run fluctuations in unemployment and 0% of the long-run fluctuations in TFP, which matches the disconnect of the short run and the long run seen in the data. Yet, the business cycle is not driven by a single, dominant, transitory shock. Instead, it is driven by two unit-root shocks, which have the same long-run effect on TFP but opposite short-run effects on unemployment.

In both of these examples the basic challenge is the same: a reduced-form shock identified via our method does not map into a "true" structural shock. Clearly, this problem is not unique to our method. For instance, the second example also invalidates the interpretation of the "demand shock" identified in Blanchard and Quah (1989), or the "technology shock" identified in Galí (1999).[31] Nevertheless, ad-

pretation is ultimately model-specific. But the use of our anatomy does extend, because the panoply of empirical restrictions contained can help model evaluation regardless of the model structure and the associated interpretation.

[31] More generally, for any "structural" shock identified in the existing SVAR literature, one can always concoct examples that deconstruct it into a combination of two or more distinct shocks, none of which resembles the object identified in the data. Whether the problem is more severe in our case depends on whether one finds the premise of a dominant business-cycle shock less defensible than those other identifying assumptions in the literature.

ditional, pertinent information can often remove this kind of challenge. Our approach provides ample such information in the form a panoply of conditional, cross-variable, static and dynamic restrictions, which can be deployed in both semi-structural and fully-structural endeavors.

To illustrate the use of our method in a semi-structural context, consider the second example. We used this example to argue that the disconnect between the short and the long run does not suffice to rule out technology, or news about it, as an important business-cycle driver. But this disconnect is not the only restriction contained in the anatomy. Another key restriction is that the MBC shock accounts for essentially zero of the TFP fluctuations at *any* horizon, including the short run. This helps reject the story proposed above: if that story were correct, the MBC shock would have been strongly correlated with current TFP, which is not the case.

We expand on this point in Appendix C. There, we impose no structure other than the assumption that TFP is driven by exactly two shocks, an unanticipated, permanent technology shock that has an immediate effect on TFP, and a news shock that has a delayed effect. We then show how two elements of our anatomy, namely the reduced-form shocks that target TFP in the short and the long run, provide an estimate of the contribution of the news shock to the unemployment fluctuations. This estimate turns out to be 13% in our baseline VAR and a bit lower in extended VARs that add stock prices.[32]

In Online Appendix I, we carry out a similar semi-structural exercise in the context of the first example: we show that the simple story of offsetting demand and supply shocks does not work insofar as the supply shock can be proxied by the reduced-form shock that captures the bulk of the TFP movements in the data. To put it differently, the supply shock has to be a markup shock. We then proceed to conduct a second, fully structural yet relatively parsimonious, exercise: we revisit the example through the lenses of a two-variable, two-shock, New Keynesian model and ask what it takes for this model to match the relevant elements of our anatomy, namely the dynamic responses of output and inflation to our identified output and inflation shocks. The answer turns out to be consistent with the interpretation of the output shock in the data as a dominant, non-inflationary demand shock in the model (and of the inflation shock as the markup shock).

All in all, these simple exercises illustrate how one can utilize additional elements of our anatomy and/or additional theoretical structure to extend the use of our method to multi-shock environments. They also serve as a prelude for the more compelling analysis in the next section, which demonstrates the effectiveness of our method in the context of three state-of-the-art DSGE models. Relative to the

[32]Another function of Appendix C is to show how the estimated contribution of the news shock depends on the number of variables included in the VAR. This corroborates a point made in Section 3.3, that our conclusions about the importance of news shocks differ from those of Beaudry and Portier (2006) in large part due to the amount of data used.

exercises discussed above, those in the next section make use of both more elaborate theoretical structures and a broader set of elements from our anatomy, which helps keep the balance between degrees of freedom and empirical restrictions.

6 An Application to Medium-Scale DSGE Models

In the previous section we argued that our method can be of use in multi-shock environments thanks to the rich set of cross-variable, dynamic restrictions it contains. In this section, we put this argument on trial by applying our method to three off-the-shelf, state-of-the-art DSGE models. This application corroborates the structural interpretation of the MBC shock suggested on the basis of single-shock models. Most importantly, it demonstrates the probing power of our method, in the sense that the conditional moments comprising the anatomy help identify flaws in the propagation mechanism of models that may have gone unnoticed before.

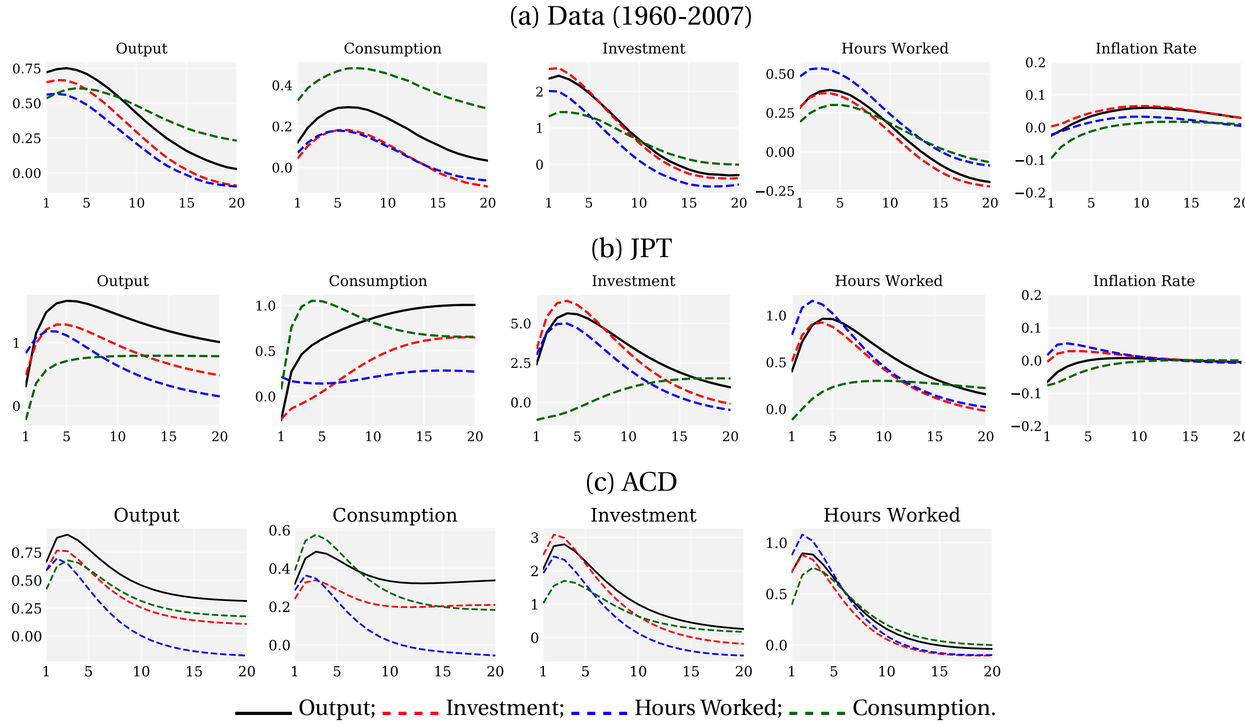
We first study the properties of the sticky-price model in Justiniano, Primiceri, and Tambalotti (2010) and the flexible-price model in Angeletos, Collard, and Dellas (2018), henceforth referred to as JPT and ACD, respectively. The first is a representative of the New Keynesian, DSGE paradigm.[33] The second is an example of a recent literature that aims at disentangling demand-driven fluctuations from nominal rigidities and Philips curves (see the references in footnote 3).

Both models have been estimated and evaluated in the respective papers using familiar, pre-existing methods.[34] The value added here is to revisit their performance through lenses of our new method. We thus take each model as is and use it to construct the linear combinations of the theoretical shocks that maximize the business-cycle volatility of GDP, investment, consumption or hours worked in the model. These objects are the theoretical counterparts to the reduced-form shocks that were previously identified in the data via our method. To avoid confusion between these objects and the primitive theoretical

[33] Indeed, it is essentially the same model as that in Smets and Wouters (2007), but with more appropriate mapping to the data. The measure of consumption used in Smets and Wouters (2007) includes expenditure on durables, which is at odds with the specification in the model. Justiniano, Primiceri, and Tambalotti (2010) fix this problem by including such expenditure to the measure of investment, just as we have done both here and in Angeletos, Collard, and Dellas (2018).

[34] In particular, both JPT and ACD have been estimated with Bayesian maximum likelihood. But whereas ACD has been estimated on the frequency domain using the levels of all variables, JPT has been estimated on the time domain using the growth rates of output, investment, and consumption. Another difference concerns the sample used: 1954Q3 to 2004Q4 in JPT vs 1960Q1-2007Q4 in ACD. As discussed later on and shown in Online Appendix J.2, re-estimating the JPT in the exact same way as ACD does not change the take-home lesson of this section. With this in mind, and to make sure that the two models are evaluated on the basis of the same sample period as that used in their estimation, the data underlying the top panels of Figure 6 refer to the VAR that appeared earlier as row [6] in Table 8, namely the one that spans the 1960Q1-2007Q4 period; as already emphasized, this makes little difference from our baseline specification.

Figure 6: The MBC Shock in the Data and the Models



shocks, we henceforth refer to the former as "factors" and reserve the term "shocks" for the latter.[35]

Figure 6 reports the IRFs of the key macroeconomic quantities and inflation to the various factors in the data (top panel) and in the two models (middle panel for JPT, bottom for ACD).[36] As seen in this figure, the various factors are highly interchangeable in ACD, as they are in the data, whereas they are quite distinct in JPT. This is most evident in the responses of output and consumption to the various factors, as well as in the comparison of the consumption factor to the other factors.[37]

We can offer a quantitative measure of these differences by constructing a metric of the interchangeability of factors in the data and in each of the models. Let $Z^{f}_{v,k}$ denote the impulse response function

[35] Our "factors" should not be confused with those in dynamic factor analysis. Also, the construction of the factors in the models abstracts from small-sample issues, because this seems ideal for revealing the theoretical mechanisms of these models. As shown in Online Appendix J.1, however, the lessons drawn below are robust to a Monte Carlo exercise that accounts for sampling uncertainly.

[36] For ACD, we omit the response of inflation because, in that model, prices are flexible and inflation is indeterminate.

[37] Another noticeable feature is the magnitude of the responses, which are roughly twice as large as in JPT than the corresponding ones in either the data or ACD. This is because the original estimation of JPT, which is based on growth rates, produces excess volatility in the levels. As can be seen in Figure 26 in Online Appendix J.2, re-estimating JPT on levels, and in the same way as in ACD, fixes this excess-volatility problem but does not overcome the interchangeability challenge. Finally, the response of inflation appears to be much more sluggish in the data than in JPT, despite the inclusion of the hybrid versions of the price and wage Philips curves. This seems interesting, although it may not be directly related to the main point we wish to make here regarding the interchangeability of factors.

of variable $v \in V$ to factor $f \in F$, where $k \geq 0$ indexes the horizon, V is the set of the four key macroeconomic quantities (output, hours, consumption, and investment), and F is the set of the corresponding four factors. Next, let $\overline{Z}_{v,k} \equiv \frac{1}{4}\sum_{f\in F} Z^f_{v,k}$ and consider the following object:

$$D_v = \frac{1}{4}\sum_{f\in F}\sqrt{\sum_{k=0}^{20}(Z^f_{v,k} - \overline{Z}_{v,k})^2}$$

This is a measure of the dispersion of the IRFs of variable v across the factors. The closer D_v is to zero, the greater the degree of interchangeability. Conversely, a large value for D_v indicates low interchangeability vis-a-vis that particular variable. Finally, let $\overline{D} \equiv \frac{1}{4}\sum_{v\in V} D_v$ This gives a metric of how interchangeable the factors are over all the variables of interest.

Table 9 reports the results of these calculations for the data and the two models (first row for the data, second row for JPT, third row for ACD). In each case, we report both the variable-specific metrics D_v (columns named "Y" through "h") and the average metric $\overline{D}$ (column named "Average"). It is evident that ACD produces nearly the same interchangeability as that observed in the data, while JPT produces much less.

Table 9: Interchangeability of Factors

	Y	C	I	h	Average
Data	0.47	0.52	1.28	0.28	0.64
JPT	2.90	2.21	6.29	1.35	3.19
ACD	0.56	0.49	1.61	0.30	0.74

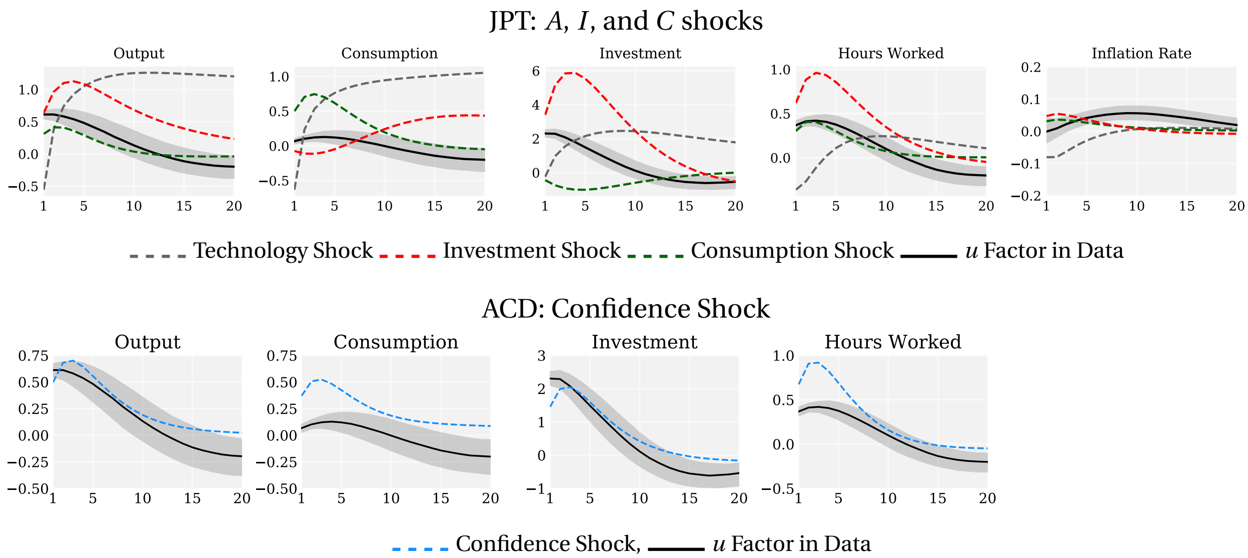
Note: This table reports the distance of factors, measured in the way described in the main text. A number closer to zero indicates a larger degree of interchangeability.

We now shed light on this result and the mechanics of the two models by doing a decomposition of their factors in terms of the underlying theoretical shocks.

Let us first consider JPT. In this model, the four macroeconomic quantities, and hence also the factors that target them, are driven by different mixtures of three distinct theoretical shocks: the investment-specific shock, the discount-factor shock, and the technology shock. As evident in the top panel of Figure 7, none of these shocks looks like the MBC shock in the data. In particular, both the investment-specific shock and consumption-specific shock induce *negative* co-movement between investment and consumption. And because each of these shocks contribute differentially to the model's factors, the latter are less interchangeable than the empirical counterparts.[38]

[38]Although the anatomy of JPT offered here is new, the basic property that the investment-specific shock in this model pro-

Figure 7: MBC Shock in Data vs Key Theoretical Shocks in JPT and ACD



Consider next ACD. In this model, all variables are driven, to a large extent, by the same shock, the confidence shock. As explained in more detail in Angeletos, Collard, and Dellas (2018), this shock is formalized as an extrinsic shock to higher-order beliefs but ultimately helps capture the following, broader mechanism: waves of optimism and pessimism about the short-term economic outlook without commensurate shifts in either TFP or the expectations of the long run. Because optimism about the short run means that firms are bullish about their returns, the demand for both capital and labor goes up. And because such optimism entails relatively small changes in expected permanent income, it induces a relatively weak wealth effect on labor supply. This bypasses the problem faced by the literature on news shocks, in which beliefs regard persistent income changes and entail large wealth effects, and allows for a positive comovement between consumption, investment and employment in the short run, even without the assistance of sticky prices and accommodative monetary policy.

What is key for the present purposes is the observation, evident in the bottom panel of Figure 7, that this shock is quite similar to the MBC shock in the data, in terms of co-movements and relative

duces negative co-movement between consumption and investment is known. This property originates in the problem first highlighted by Barro and King (1984) and would have been even sharper if were not for the following three model ingredients: time-non-separable preferences, sticky prices, and a monetary policy that induces an expansion relative to flexible prices. Most of the existing attempts to fix the negative comovement problem maintain all three ingredients (Furlanetto, Natvik, and Seneca, 2013; Ascari, Phaneuf, and Sims, 2016). Molavi (2019) maintains the last two of them, sticky prices and accommodative monetary policy, but adds a belief-based mechanism that, at least in principle, appears to have the potential of generating the requisite comovement even with flexible prices. An evaluation of the relative merits of these works vis-a-vis ACD, whose good comovement properties do not rely on any of the aforementioned DSGE features, or any other member of the flexible-price literature cited in footnote 3 is clearly beyond the scope of this paper.

volatilities. This helps explains why the factors in ACD are almost as interchangeable as those in the data. Basically, this is because a bare-bones version of ACD, which shuts down all shocks except the confidence shock, achieves perfect interchangeability without a big sacrifice in terms of matching the MBC shock in the data—a property clearly not shared by any single-shock restriction of JPT and any other leading DSGE model we are aware of.

These lessons are robust to two additional exercises, which are reported in Online Appendix J.2. In the first, we re-estimate JPT with the same frequency-domain method as that used in the estimation of ACD. In the second exercise, we re-estimate both JPT and ACD on the basis of our anatomy, namely by minimizing the distance of each model from the data in terms of the impulse responses of the output, consumption, investment, and hours to the four factors that target the same quantities. Both exercises help JPT produce more interchangeability, but the model still falls short of that found in the data as well as of that produced by the ACD model.

That said, the goal of these exercises is not to argue that ACD is superior to JPT, but rather to illustrate the probing power of our empirical method and to give guidance to future research. In the same vein, we have applied our method to another important DSGE model, that of Christiano, Motto, and Rostagno (2014), henceforth CMR.

This model is on the forefront of a new strand of the DSGE literature that pays close attention to the real-financial nexus. Its main differences from the model used in Christiano, Eichenbaum, and Evans (2005) and Justiniano, Primiceri, and Tambalotti (2010) are the following three. First, it includes a financial friction that constrains investment, the latter been broadly defined to include consumer durables. Second, it contains a new structural shock ("risk shock") that determines the severity of the financial friction.[39] And third, it uses financial variables, most notably the credit spread between the gross nominal interest rate on debt and the risk free rate and the level of credit to such firms in the estimation and validation of the model.

The anatomy of this model involves not only the behavior of the macroeconomic quantities we have focused on so far, but also that of the new, financial variables. We have thus extended our anatomy of the data in Online Appendix G.3 to include information about these variables.[40]

[39]To be precise, this shock comes in nine flavors, depending on whether it hits the idiosyncratic volatility of firm returns with a lag of 0, 1, 2,. . . 8 quarters.

[40]This is done in Online Appendix G.3 using three complementary VARs. The first one is obtained by adding only the credit spread to our baseline VAR. This allows us to keep the original sample size and corresponds to what is reported as row 10 in Tables 8 and 20–23. The second is obtained by adding all the four financial variables used in CMR. In this case, data limitations force a shorter sample, 1971Q1-2014Q4. The third is obtained by restricting the second VAR to 1985Q1-2010Q4, which is the sample period used in the original estimation of CMR. The three VARs produce similar results, underscoring the robustness not only of our main findings but also of the additional findings reported in Figure 8 regarding the real-financial nexus.

Figure 8: Comparing Business-Cycle Factors

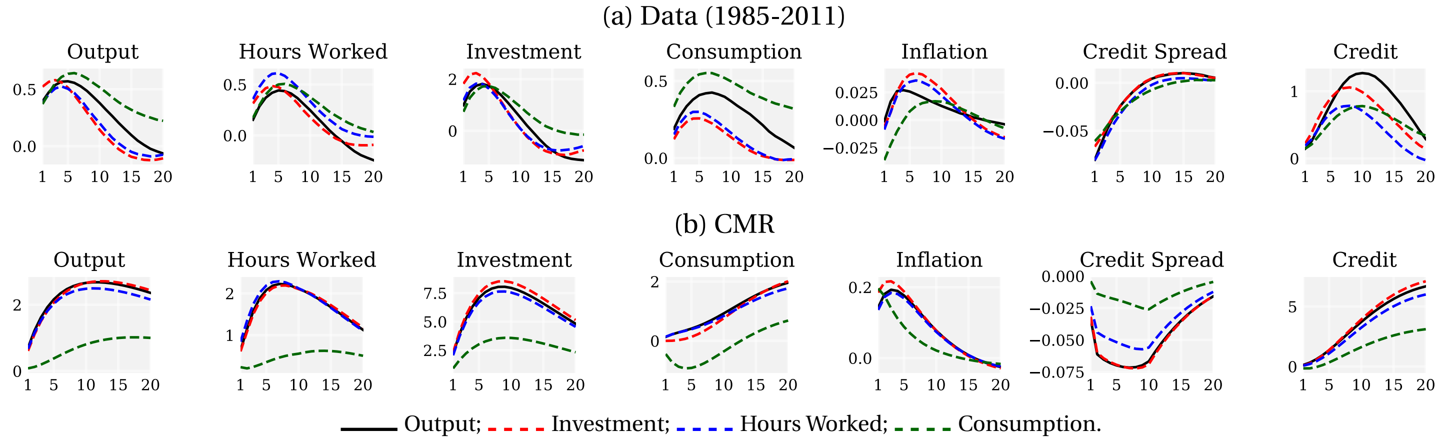


Figure 8 conducts a similar exercise as Figure 6. The top panel reports the IRFs of a few key variables to the output, hours, investment and consumption factors. The bottom panel reports the corresponding objects in the model. The only changes are the use of CMR instead of JPT or ACD; the focus on the sub-sample used in the estimation of that model;[41] and the addition of the impulse responses of the credit spread and the level of credit.

The following four patterns emerge. First, CMR improves upon JPT in terms of featuring more interchangeability between the output, hours, and investment factors—actually too much of it. Second, CMR does worse than JPT in terms of missing the business-cycle properties of consumption. This is evident both in the response of consumption to the aforementioned factors and in the response of all variables to the consumption factor. Third, CRM produces too much volatility and persistence compared to the data. Fourth, despite its use of a very flat Philips curve and very sticky wages, CMR produces a much steeper relation between inflation and real economic activity than that seen in the data, underscoring its reliance on nominal rigidity. Last but not least, the model fails to capture the dynamics of the response of the credit spread to all of these factors: while in the data the credit spread appears to lead the MBC shock, in the sense that it peaks before the macroeconomic quantities, it does the opposite in the model.

Whether these patterns represent critical failures for the CMR's ability to capture the propagation of business cycles or easily fixable weaknesses is an open question beyond the scope of our paper.[42] As

[41] That is, the empirical IRFs are obtained by using the last of the three VARs mentioned in footnote 40 above. Similarly to what we did in the case of JPT and ACD, this ensures that the model is evaluate on the basis of the period used in its estimation. But as already mentioned, the empirical patterns themselves are robust to the longer period spanned by our baseline specification.

[42] The excessive persistence appears to be the product of the model's reliance on an unusually high adjustment cost for investment and very persistent shocks. The property that the business cycle leads, rather than lags, the credit spread appears to be driven by the model's reliance on a number of news shocks, which have a relatively more pronounced and front-loaded effect on investment, hours and output than on the credit spread. We do not know how changing these features would impact on the

already noted, the main goal of all the exercises conducted in this section is to illustrate the probing power of our method in the context of state-of-the-art, medium-scale models.

7 Conclusion

We have proposed a new strategy for dissecting macroeconomic time series and have used its findings to guide theory. The strategy involves employing a VAR to construct a collection of reduced-form shocks, each of which maximizes the volatility of a particular variable at particular frequencies. This yields a rich set of one-dimensional cuts of the data, which we call the anatomy of the data.

Prominent elements of this anatomy are the shocks that target unemployment, output, hours worked, investment and consumption at the business-cycle frequencies. The near interchangeability of these objects in terms of IRFs motivates the concept of the MBC shock: we use this term to refer to the dynamic comovement patterns that are common to all these cuts of the data. These include a strong, positive, and transient comovement between the aforementioned quantities; little relation with both inflation and TFP at any horizon; and a disconnect between the short run and the long run.

We have argued that these patterns speak against theories that seek to attribute the bulk of the business cycle to any of the following forces: technology shocks; financial, uncertainty and other shocks that matter primarily by affecting aggregate TFP; news about medium- to long-run productivity prospects; and inflationary demand shocks. In contrast, models that contain a non-inflationary demand shock as the main driver of the business cycle seem a priori consistent with this evidence.

This conclusion is based on the premise that the bulk of the business cycle can be attributed to a single shock or, equivalently, by a dominant propagation mechanism shared by multiple shocks. But even if this is not the case, the rich set of the dynamic comovement patterns that comprise our MBC shock, or more generally, our anatomy, serve as useful yardstick for model evaluation: models of any size and complexity can be readily confronted with these patterns. Prominent members of the DSGE literature have difficulty passing this test, despite the inclusion of a flat Philips curve and other ingredients that enhance model fit.

We have interpreted our empirical findings as an indication that the flexible-price core of the mainstream, New Keynesian framework needs to be amended so as to accommodate demand-driven business cycles without nominal rigidities, in line with the theoretical literature cited in footnote 3. We hope that the characterization of the data performed in the present paper will stimulate further research in this direction, or otherwise guide macroeconomic theory.

empirical performance of the model along other dimensions and also on the structural interpretation offered to the data.

Finally, while our anatomy is quite comprehensive, it could be further enriched by more refined cuts of the data. Consider, in particular, the following enrichment. For each variable $X \in \{u, Y, h, I, C\}$, first filter out the effect of the shock that accounts for most of the business-cycle volatility in that variable (i.e., the kind of shock we have focused in this paper) and then construct the shock that accounts for most of the *residual* volatility in the same variable. This procedure gives the "second largest shocks" corresponding to the main macroeconomic quantities. We find that these shocks display a similar interchangeability property as the one that motivated our concept of the MBC shock. They can thus be thought of as different facets of the same, secondary, business-cycle shock (subject, of course, to the same kind of interpretation challenges as those discussed in Section 5). Online Appendix K details the empirical profile of this shock, compares it to that of the MBC shock, and illustrates how this could serve as an additional model-validation tool.

References

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas. 2015. "Quantifying Confidence." Tech. Rep. 20807, National Bureau of Economic Research.

———. 2018. "Quantifying Confidence." *Econometrica* 86 (5):1689–1726.

Angeletos, George-Marios and Jennifer La'O. 2010. "Noisy Business Cycles." In *National Bureau of Economic Research Macroeconomics Annual 2009, Volume 24*. University of Chicago Press, 319–378.

———. 2013. "Sentiments." *Econometrica* 81 (2):739–779.

Arellano, Cristina, Yan Bai, and Patrick Kehoe. 2019. "Financial Frictions and Fluctuations in Volatility." *Journal of Political Economy* 127 (5):2049–2103.

Ascari, Guido, Louis Phaneuf, and Eric Sims. 2016. "Business Cycles, Investment Shocks, and the "Barro-King" Curse." *National Bureau of Economic Research Working Paper* (22941).

Bai, Yan, José-Vıctor Ríos-Rull, and Kjetil Storesletten. 2017. "Demand Shocks as Productivity Shocks." .

Barro, Robert J. and Robert G. King. 1984. "Time-Separable Preferences and Intertemporal-Substitution Models of Business Cycles." *The Quarterly Journal of Economics* 99 (4):817–839.

Barsky, Robert B. and Eric R. Sims. 2011. "News Shocks and Business Cycles." *Journal of Monetary Economics* 58 (3):273 – 289.

Beaudry, Paul, Dana Galizia, and Franck Portier. 2018. "Reconciling Hayek's and Keynes' Views of Recessions." *The Review of Economic Studies* 85 (1):119–156.

Beaudry, Paul and Franck Portier. 2006. "Stock Prices, News, and Economic Fluctuations." *American Economic Review* 96 (4).

———. 2014. "Understanding Noninflationary Demand-Driven Business Cycles." *National Bureau of Economic Research Macroeconomics Annual* 28 (1):69–130.

———. 2018. "Real Keynesian Models and Sticky Prices." Working Paper 24223, National Bureau of Economic Research.

Benhabib, Jess and Roger E. A. Farmer. 1994. "Indeterminacy and Increasing Returns." *Journal of Economic Theory* 63 (1):19–41.

Benhabib, Jess, Pengfei Wang, and Yi Wen. 2015. "Sentiments and Aggregate Demand Fluctuations." *Econometrica* 83 (2):549–585.

Blanchard, Olivier J. and Danny Quah. 1989. "The Dynamic Effects Of Aggregate Demand And Supply Disturbances." *American Economic Review* 79 (4):655–673.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. 2018. "Really Uncertain Business Cycles." *Econometrica* 83 (3):1031–1065.

Canova, Fabio. 2007. *Methods for Applied Macroeconomic Research.* Princeton University Press.

Chahrour, Ryan and Kyle Jurado. 2018. "News or Noise? The Missing Link." *American Economic Review* 108 (7):1702–36.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy* 113 (1):1–45.

Christiano, Lawrence J. and Terry J. Fitzgerald. 2003. "The Band Pass Filter." *International Economic Review* 44 (2):435–465.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review* 104 (1):27–65.

Cochrane, John H. 1994. "Shocks." *Carnegie-Rochester Conference Series on Public Policy* 41:295 – 364.

Debortoli, Davide, Jordi Galí, and Luca Gambetti. 2019. "On the Empirical (Ir)Relevance of the Zero Lower Bound Constraint." Working Paper 25820, National Bureau of Economic Research.

Diamond, Peter A. 1982. "Aggregate Demand Management in Search Equilibrium." *The Journal of Political Economy* :881–894.

Eusepi, Stefano and Bruce Preston. 2015. "Consumption Heterogeneity, Employment Dynamics and Macroeconomic Co-movement." *Journal of Monetary Economics* 71 (C):13–32.

Faust, Jon. 1998. "The robustness of identified VAR conclusions about money." *Carnegie-Rochester Conference Series on Public Policy* 49:207 – 244.

Fernald, John G. 2012. "A Quarterly, Utilization-adjusted Series on Total Factor Productivity." Working Paper Series 2012-19, Federal Reserve Bank of San Francisco.

Forni, Mario, Luca Gambetti, and Luca Sala. 2019. "Structural VARs and Non-invertible Macroeconomic Models." *Journal of Applied Econometrics* 34 (2):221–246.

Francis, Neville, Michael T. Owyang, Jennifer E. Roush, and Riccardo DiCecio. 2014. "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks." *The Review of Economics and Statistics* 96 (4):638–647.

Furlanetto, Francesco, Gisle J. Natvik, and Martin Seneca. 2013. "Investment shocks and macroeconomic co-movement." *Journal of Macroeconomics* 37:208 – 216.

Galí, Jordi. 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review* 89 (1):249–271.

Galí, Jordi and Mark Gertler. 1999. "Inflation Dynamics: A Structural Econometric Analysis." *Journal of Monetary Economics* 44 (2):195–222.

Golosov, Mikhail and Guido Menzio. 2015. "Agency Business Cycles." Working Paper 21743, National Bureau of Economic Research.

Guesnerie, Roger and Michael Woodford. 1993. "Endogenous Fluctuations." In *Advances in Economic Theory*, vol. 2, edited by Jean-Jacques Laffont. Cambridge University Press, 289–412.

Huo, Zen and Naoki Takayama. 2015. "Higher Order Beliefs, Confidence, and Business Cycles." miméo, Yale University.

Ilut, Cosmin and Hikaru Saijo. 2018. "Learning, Confidence, and Business Cycles." miméo, Duke University.

Jaimovich, Nir and Sergio Rebelo. 2009. "Can News about the Future Drive the Business Cycle?" *American Economic Review* 99 (4):1097–1118.

Johansen, S. and K. Juselius. 1990. "Maximum Likelihood Estimation and Inference on Cointegration with Applications to Demand for Money." *Oxford Bulletin of Economics and Statisticss* 52 (2):169–210.

Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti. 2010. "Investment Shocks and Business Cycles." *Journal of Monetary Economics* 57 (2):132–145.

Koop, Gary. 2003. *Bayesian Econometrics.* John Wiley & Sons.

Kydland, Finn E and Edward C Prescott. 1982. "Time to Build and Aggregate Fluctuations." *Econometrica* 50 (6):1345–1370.

Lorenzoni, Guido. 2009. "A Theory of Demand Shocks." *American Economic Review* 99 (5):2050–84.

Lucas, Robert E. Jr. 1975. "An Equilibrium Model of the Business Cycle." *Journal of Political Economy* 83 (6):1113–44.

———. 1977. "Understanding Business Cycles." *Carnegie-Rochester Conference Series on Public Policy* 5:7 – 29.

Mavroeidis, Sophocles, Mikkel Plagborg-Møller, and James H. Stock. 2014. "Empirical Evidence on Inflation Expectations in the New Keynesian Phillips Curve." *Journal of Economic Literature* 52 (1):124–88.

Molavi, Pooya. 2019. "Macroeconomics with Learning and Misspecification: A General Theory and Applications." miméo, MIT.

Ramey, Valerie A. 2016. *Macroeconomic Shocks and Their Propagation*, *Handbook of Macroeconomics*, vol. 2, chap. 2. Elsevier, 71–162.

Smets, Frank and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review* 97 (3):586–606.

Stock, James H. and Mark W. Watson. 1999. "Business Cycle Fluctuations in US Macroeconomic Time Series." In *Handbook of Macroeconomics*, *Handbook of Macroeconomics*, vol. 1, edited by J. B. Taylor and M. Woodford, chap. 1. Elsevier, 3–64.

Uhlig, Harald. 2003. "What Moves Real GNP?" mimeo.

APPENDICES

A Data

The data is from the Federal Reserve Economic Database (FRED). TFP corresponds to the TFP time series corrected for utilization produced by Fernald (2012) (downloaded 2016). Tables 10 and 11 describe the original data and the transformations used in our VARs. Table 12 reports the raw (unconditional) correlations over the business-cycle frequencies.

Table 10: Description of Data

Data	Mnemonic	Freq.	Transform
Real gross domestic product per capita	A939RX0Q048SBEA	Q	–
Gross Domestic Product	GDP	Q	–
Gross Domestic Product: Implicit Price Deflator	GDPDEF	Q	–
Personal Consumption Expenditures: Nondurable Goods	PCND	Q	–
Personal Consumption Expenditures: Services	PCESV	Q	–
Personal Consumption Expenditures: Goods	PCDG	Q	–
Gross Private Domestic Investment	GPDI	Q	–
Nonfarm Business Sector: Real Output Per Hour of All Persons	OPHNFB	Q	–
Nonfarm Business Sector: Labor Share	PRS85006173	Q	–
Nonfarm Business Sector: Average Weekly Hours	PRS85006023	Q	–
Civilian Noninstitutional Population	CNP16OV	M	EoP
Civilian Unemployment Rate	UNRATE	M	Ave
Effective Federal Funds Rate	FEDFUNDS	M	Ave
Total Factor Productivity (Growth rate)	DTFPu	Q	–

Note: Q: Quarterly, M: Monthly, EoP: end of period, Ave: quarterly average.

Table 11: Variables in the VARs

Real GDP per capital	`Y=log(A939RX0Q048SBEA)`
Real consumption per capita	`C=log((PCND+PCESV)*A939RX0Q048SBEA/GDP)`
Real investment per capita	`I=log((PCDG+GPDI)*A939RX0Q048SBEA/GDP)`
Hours worked	`H=log(PRS85006023*CE16OV/CNP16OV)`
Inflation Rate	π`=log(GDPDEF/GDPDEF(-1)`
Interest Rate	`R=FEDFUNDS/400`
Productivity (NFB)	`YSHnfb=OPHNFB`
Labor Share	`wh/y=log(PRS85006173)`
TFP	`TFP=log(cumulative sum (DTFPu/400))`

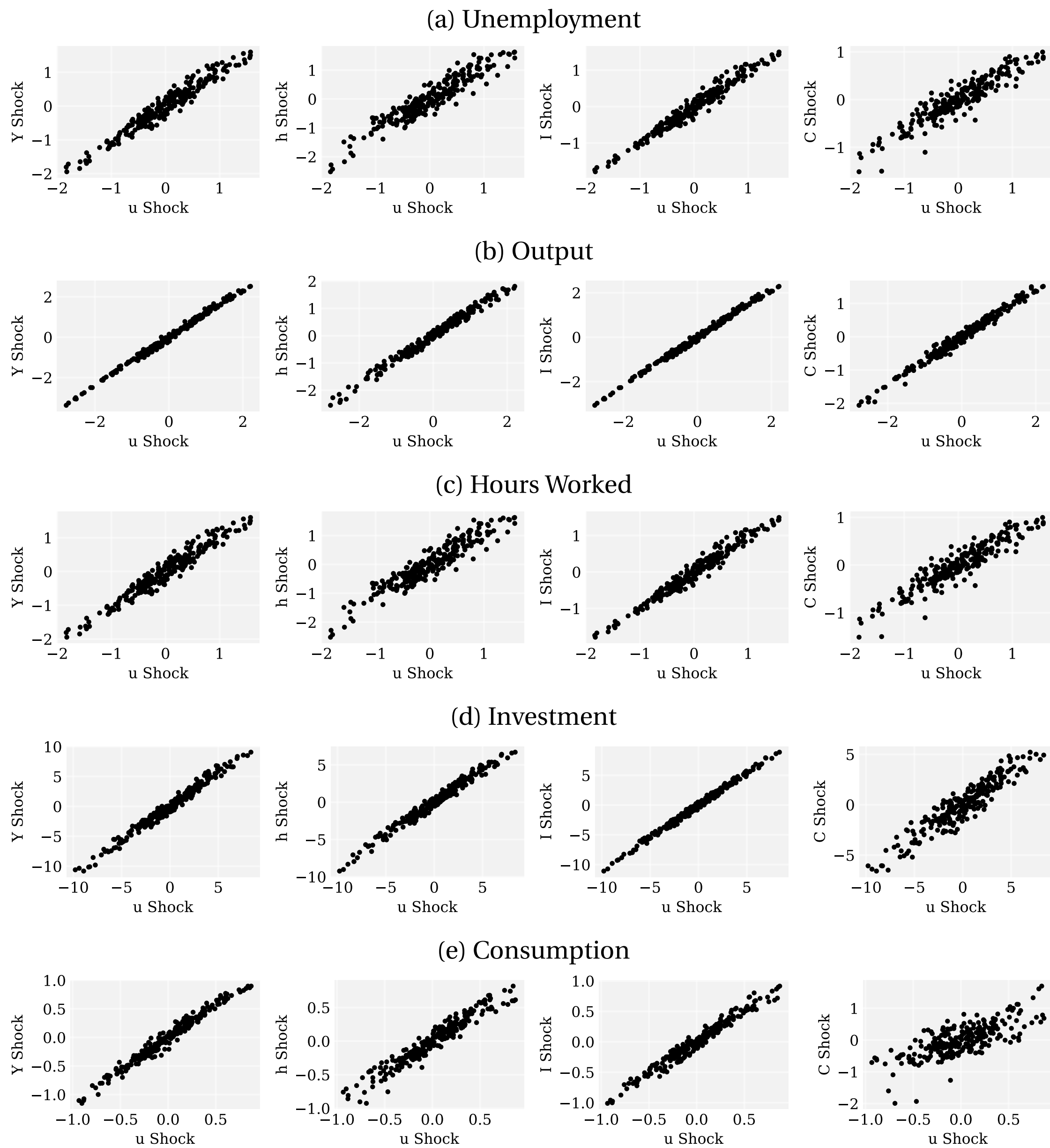
Table 12: Correlations (Bandpass filtered, 6-32 Quarters)

	Y_t	C_t	I_t	h_t	u_t	TFP_t	$(Y/h)_t$	$(Wh/Y)_t$	π_t	R_t
Y_t	1.00	0.84	0.95	0.89	-0.88	-0.19	0.47	-0.15	0.21	0.40
C_t	0.84	1.00	0.76	0.82	-0.78	-0.28	0.24	0.05	0.31	0.42
I_t	0.95	0.76	1.00	0.89	-0.85	-0.24	0.44	-0.18	0.13	0.33
h_t	0.89	0.82	0.89	1.00	-0.93	-0.46	0.11	0.06	0.29	0.47
u_t	-0.88	-0.78	-0.85	-0.93	1.00	0.41	-0.06	-0.16	-0.37	-0.59
TFP_t	-0.19	-0.28	-0.24	-0.46	0.41	1.00	0.45	-0.23	-0.27	-0.34
$(Y/h)_t$	0.47	0.24	0.44	0.11	-0.06	0.45	1.00	-0.56	-0.30	-0.31
$(Wh/Y)_t$	-0.15	0.05	-0.18	0.06	-0.16	-0.23	-0.56	1.00	0.31	0.23
π_t	0.21	0.31	0.13	0.29	-0.37	-0.27	-0.30	0.31	1.00	0.72
R_t	0.40	0.42	0.33	0.47	-0.59	-0.34	-0.31	0.23	0.72	1.00

B Interchangeability in the Time Series

In the main text we emphasized the interchangeability of the various facets of the MBC shock in terms of IRFs. Figure 9 shows that a similar interchangeability property is present in terms of the time series generated by the reduced-form shocks. Each row in this figure reports, for each one of the key macroeconomic quantities, the scatterplot of that variable as predicted by the Y, I, C, and h shocks against its value as predicted by the unemployment shock. Table 3 in the main text summarizes the information contained in this figure in terms of correlations.

Figure 9: The Various Facets of the MBC Shock, Scatterplots



C Application to New Shocks

In this Appendix, we use our method to identify news shocks and examine how their properties, in particular their contribution to business cycles, vary with the size of the VAR used to identify the shocks. This serves two purposes. It sheds light on the source of the difference reported in the main text between our findings and those of Beaudry and Portier (2006). And it provides yet another example of the usefulness of our method outside the realm of one-shock representations of the business cycle, in particular, in the context of semi-structural explorations.

The exercise conducted here is based on the premise that the vast majority, if not all, of the TFP fluctuations at all frequencies can be accounted by two structural shocks: an unanticipated, permanent shock and a news shock. The former affects TFP both in the short and the long run, while the latter does not have an effect on impact.[43]

As explained in Section 5, the accommodation of these two structural shocks complicates the interpretation of the empirical MBC shock and in particular of its disconnect from the long run: this disconnect is consistent with models in which the two structural shocks under consideration have significant but offsetting effects on unemployment in the short run. Still, insofar as only these two shocks drive TFP, and regardless of how many other shocks may drive unemployment, we can identify the news shock and its business-cycle contribution as follows.

We first construct, via our method, the two empirical shocks that have the maximal contribution to the volatility of TFP in the long-run and the business-cycle frequencies ($80-\infty$ and $6-32$ quarters, respectively). Denote these by s_t^1 and s_t^2, respectively. These shocks do not have a structural interpretation but are linear combinations of the two "true" structural shocks, the unanticipated technology shock, s_t^{tech}, and the news shock, s_t^{news}. The two sets of shocks are related as follows:

$$\begin{bmatrix} s_t^1 \\ s_t^2 \end{bmatrix} = A \begin{bmatrix} s_t^{tech} \\ s_t^{news} \end{bmatrix}$$

for some matrix A. As long as both s_t^1 and s_t^2 have a non-zero impact effect on TFP (which is true for all the specifications considered below), one can construct their unique (up to rescaling) linear combination that has a zero impact effect on TFP. This combination recovers the news shock.

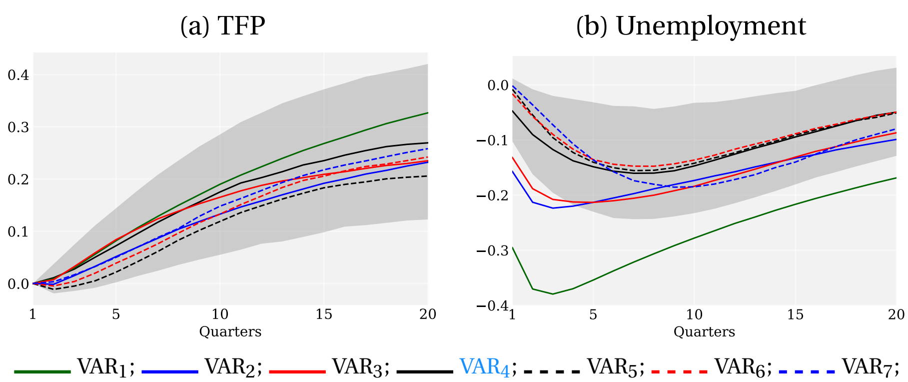
We have implemented this identification strategy in our baseline VAR, as well as in several other smaller and larger VARs. We report results below for seven nested specifications, denoted as VAR_1 through

[43] One may object to the assumption of only two TFP shocks, on the basis, for instance, that the "right" model features multiple news shocks, each one corresponding to different horizons at which TFP is expected to change. But this is a slippery road that ultimately leads one to give up hope on "a-theoretic" endeavors and, instead, commit to a particular, fully-specified model. Clearly, each approach has its strengths and limitations. We follow the one approach here and the other in Section 5.

VAR$_7$. The smallest one, VAR$_1$, contains only the main two variables of interest, TFP and unemployment. VAR$_2$ adds investment. VAR$_3$, adds GDP, consumption and hours, giving the "real core" of our baseline VAR. The latter is herein denoted by VAR$_4$; this contains all the 10 variables described in Section 2. VAR$_5$ adds the SP500 index. VAR$_6$ adds capacity utilization. VAR$_7$ adds the credit spread.

In all of the VARs, the two empirical shocks, s_t^1 and s_t^2, together account for for over 95% of the volatility of TFP at the long-run frequencies and for over 85% of that at the business-cycle frequencies. In our baseline specification, in particular, these numbers are 99% and 92%, respectively. In this regard, our two-shock representation of TFP works well. Moreover, the effect of the identified news shock on the dynamics of TFP is quite similar across the VARs: see the left panel of Figure 10. Such robustness, however, is absent in the relationship between news shocks and unemployment fluctuations; see the right panel of Figure 10. In particular, the news shock switches from being strongly expansionary in the smallest VAR to being sligtly contractionary in the largest VAR.

Figure 10: IRF of TFP and Unemployment to News Shock



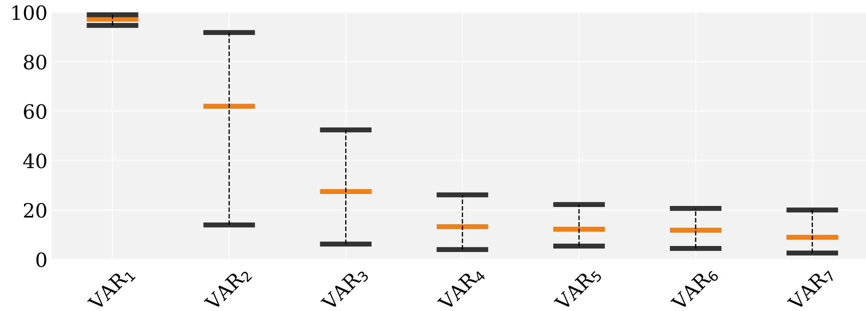
Shaded area: 68% HPDI for VAR$_4$ (baseline)

Figure 11 presents this sensitivity in terms of the contribution of the identified news shock to the volatility of unemployment at the business-cycle frequencies. On the horizontal axis, we vary the size of the VAR used in the construction of s_t^1 and s_t^2 and, thereby, of the news shock: as we move from left to right, we progressively add more data and, accordingly, increase the size of the VAR from 2 variables to a total of 13.

The figure speaks for itself: as more information (in the form of the additional variables) is incorporated, the estimated contribution of the news shock declines dramatically, stabilizing at around 11% in the last four specifications. In our baseline specification, the number is 13%.

Due to the well-known potential fragility of results from small VARs (Forni, Gambetti, and Sala, 2019), we trust more the results from the medium and larger ones, specially because size seizes to matter after

Figure 11: Variance Contribution of News Shock to Unemployment



Note: Contribution of news shock to unemployment at business-cycle frequencies. Red line gives median, upper and lower black lines give 68% HPDI. $\text{VAR}_1 = \{u, \text{TFP}\}$, $\text{VAR}_2 = \text{VAR}_1 \cup \{I\}$, $\text{VAR}_3 = \text{VAR}_2 \cup \{Y, C, h\}$, VAR_4 = Baseline VAR, $\text{VAR}_5 = \text{VAR}_4 \cup \{SP500\}$, $\text{VAR}_6 = \text{VAR}_5 \cup \{\text{utilization}\}$, $\text{VAR}_7 = \text{VAR}_6 \cup \{\text{credit spread}\}$.

a certain size. Larger VARs contain more information, while smaller ones may mechanically attribute a larger share of the business cycle to the news shock.

To illustrate the latter point, consider VAR_1. In this specification, the news shock accounts for 97% of the short-run fluctuations in unemployment. Why? In a two variables-two shocks specification, s_t^{tech} and s_t^{news} must together account for all of the fluctuations in unemployment. Due to the assumption that s_t^{tech} is the only shock that has an immediate, impact effect on TFP, s_t^{tech} is closely associated with actual TFP in the short run. But as we have established, TFP is nearly orthogonal to unemployment at the business-cycle frequencies (and beyond). It then follows that s_t^{tech} can account for only a trivial fraction of the unemployment fluctuations—which leaves s_t^{news} as the only shock to explain unemployment fluctuations. In short, this VAR mechanically attributes a large fraction of the business cycle to the news shock, simply because the only other allowed shock is a "dead horse" to start with.

As we move to larger VARs, we add more data but also more shocks that can contribute to the fluctuations in unemployment. So the role of news is bound to wither. Figure 11 shows that the decline is precipitous at first, but stabilizes once we reach the baseline specification.

This helps shed light on the main reason why our results differ from those in Beaudry and Portier: we use larger VARs than they do. Another part of the difference comes from using different identifying assumptions.

The exercise conducted here also serves another important purpose. Namely, it helps showcase the usefulness of our approach in the realm of multi-shock models without a need for the explicit intermediation of a particular, fully-specified model. The key is to drop the exclusive focus on the MBC shock and include other features of the anatomy—here for instance the shocks that target TFP in the short and the long run—and to utilize the cross-equation restrictions associated with them. As shown in Section 6, the same procedure also proves very effective in the context of fully-structural endeavors.

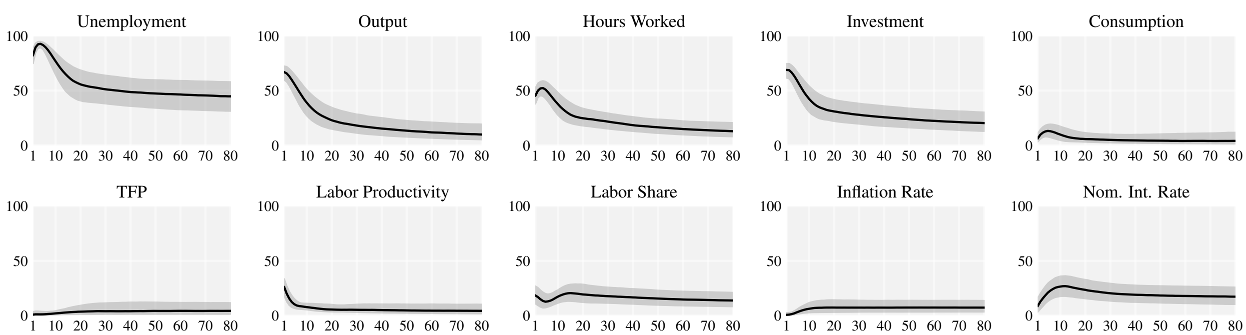
ONLINE APPENDICES

D Variance Contributions in the Time Domain

Figure 12 complements Table 1 in the main text by reporting the contribution of the identified MBC shock to the FEV of the variables at different horizons. To avoid any confusion, let us emphasize that the shock is still identified in the frequency domain, by targeting the volatility of unemployment over the band of the business-cycle frequencies. The time domain is used only in the calculation of variance contributions.

The picture that emerges is fully consistent with that painted in the main text: the identified shock explain the bulk of the short-run variation in the key macroeconomic quantities, and has a negligible footprint to TFP and inflation at all horizons. The only subtlety worth noting here is that "short run" in the time domain maps to a horizon of about 4 to 8 quarters. This is evident not only in the FEV contributions reported here but also in the IRFs shown in the main text, which pick within the first few quarters. And it anticipates the choice of the horizon targeted in a variant, time-domain identification considered in Online Appendix E.

Figure 12: Variance Contributions at Different Horizons



Note: Variance contributions of the MBC shock in the time domain. Horizontal axis: time horizon in quarters. Shaded area : 68% HPDI.

E Business Cycles in the Frequency vs Time Domain

In this appendix we explore how our method, which identifies the MBC shock in the frequency domain, maps to the time domain. In the first part, we use a simple model to illustrate why targeting the 6-32 quarters range in the frequency domain (FD) is not tautologically the same as targeting the 6-32 quarters horizon range in the time domain (TD). In that model, the shock that targets 6-32 quarters range in the

FD is instead best proxied by the shock that targets 4 quarters in the TD. The second part completes the picture by showing how these properties characterizes the actual data as well.

E.1 Time Domain vs Frequency Domain: A Simple Theoretical Example

In this section we use a 3 equation-3 shock model as a laboratory for investigating the relation between MBC shock identification in the frequency and time domain. The properties of the primitive shocks are chosen in a way that the model gives rise to an MBC shock that replicates our identified empirical MBC shock in the frequency domain (maximizes contribution to volatility of certain variables over the band of 6-32 quarters). We then derive two shocks in the time domain: One by targeting FEVs at 4 quarters; and another by targeting FEVs over the horizons 6-32 quarters. We then compare the properties of the FD MBC shock to those derived in the time domain. The objective of this subsection is to establish that targeting FEV at 4 quarters in the time domain gives rise to the same object as targeting volatility in the band of 6-32 quarters produces; while targeting FEVs over the 6-32 quarter horizons produces a distinctly different object (something that exerts relatively little influence in the short run but has more important effects in the medium term).

Let us consider a model featuring 3 shocks ($x_{i,t}$, i=1,2,3)

$$\begin{aligned} x_{1,t} &= \varphi_1 x_{1,t-1} + \varphi_2 x_{1,t-2} + \varepsilon_{1,t} \\ x_{2,t} &= \rho x_{2,t-1} + \varepsilon_{2,t} \\ \Delta x_{3,t} &= \varrho \Delta x_{3,t-1} + \varepsilon_{3,t} \end{aligned}$$

where, without loss of generality, $\varepsilon_t \equiv (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}) \rightsquigarrow \mathcal{N}(0, I)$. In the sequel, we set $\varphi_1 = 1.55$ and $\varphi_2 = 0.6$ such that the AR(2) model displays persistence and generates a hump in the response to a $\varepsilon_{1,t}$ shock in period 4. The persistence of the $x_{2,t}$ shock is set to $\rho = 0.25$ such that the shock is stationary and displays low persistence. Finally, we used $\varrho = 0.8$, such that the diffusion is slow but the bulk of it has taken place in quarter 32.

Endogenous variables ($y_{i,t}$, i=1,2,3) are then determined by

$$y_{i,t} = x_{1,t} + a_i x_{2,t} + b_i x_{3,t}$$

The coefficients a_i and b_i are determined such that the contribution of the various shocks to the volatility of y_i are as reported in Table 13.

Thus, x_2 is the MBC shock, y_1 and y_2 correspond to macroeconomic quantities such as output and employment and y_2 could be a variable such as inflation.

Table 13: Variance contribution of "structural" shocks (6-32 Quarters)

	y_1	y_2	y_3
x_1	75.00	60.00	10.00
x_2	15.00	10.00	80.00
x_3	10.00	30.00	10.00

Table 14: Variance Contribution of Identified Shocks

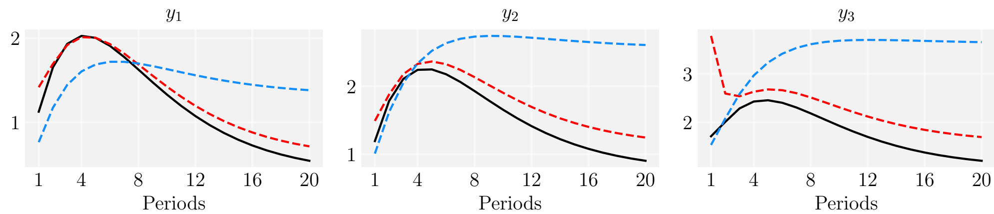
	Targeting y_1			Targeting y_2			Targeting y_3		
	y_1	y_2	y_3	y_1	y_2	y_3	y_1	y_2	y_3
FD	80.47	73.12	13.80	74.30	78.54	16.36	16.25	11.96	81.47
TD 4	76.70	74.05	18.07	65.88	75.16	17.25	17.01	11.88	75.90
TD 6-32	37.87	59.31	15.21	20.13	42.86	12.61	16.17	38.10	11.09

Table 15: Structural Decomposition of Identified Shocks

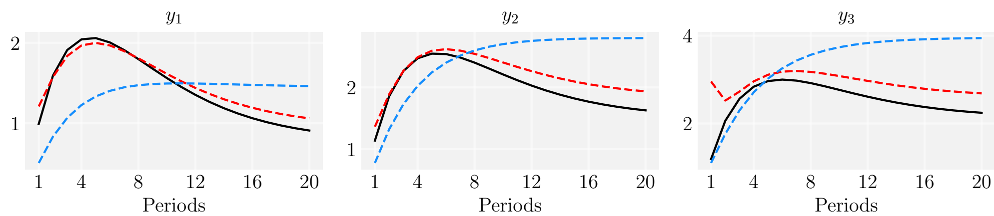
	Targeting y_1			Targeting y_2			Targeting y_3		
	x_1	x_2	x_3	x_1	x_2	x_3	x_1	x_2	x_3
FD	98.98	0.05	0.97	95.14	0.00	4.86	0.69	98.12	1.19
TD 4	96.41	1.18	2.41	90.59	0.67	8.74	9.75	89.11	1.15
TD 6-32	64.45	0.07	35.48	23.82	0.01	76.17	12.88	0.47	86.65

Figure 13: IRF to Identified Shocks

(a) Targeting y_1



(b) Targeting y_2



(c) Targeting y_3

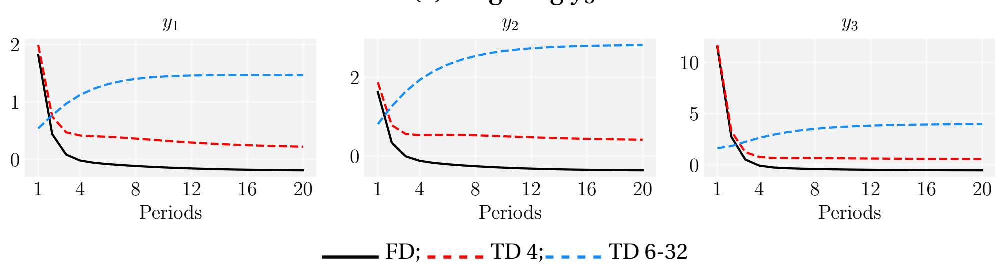
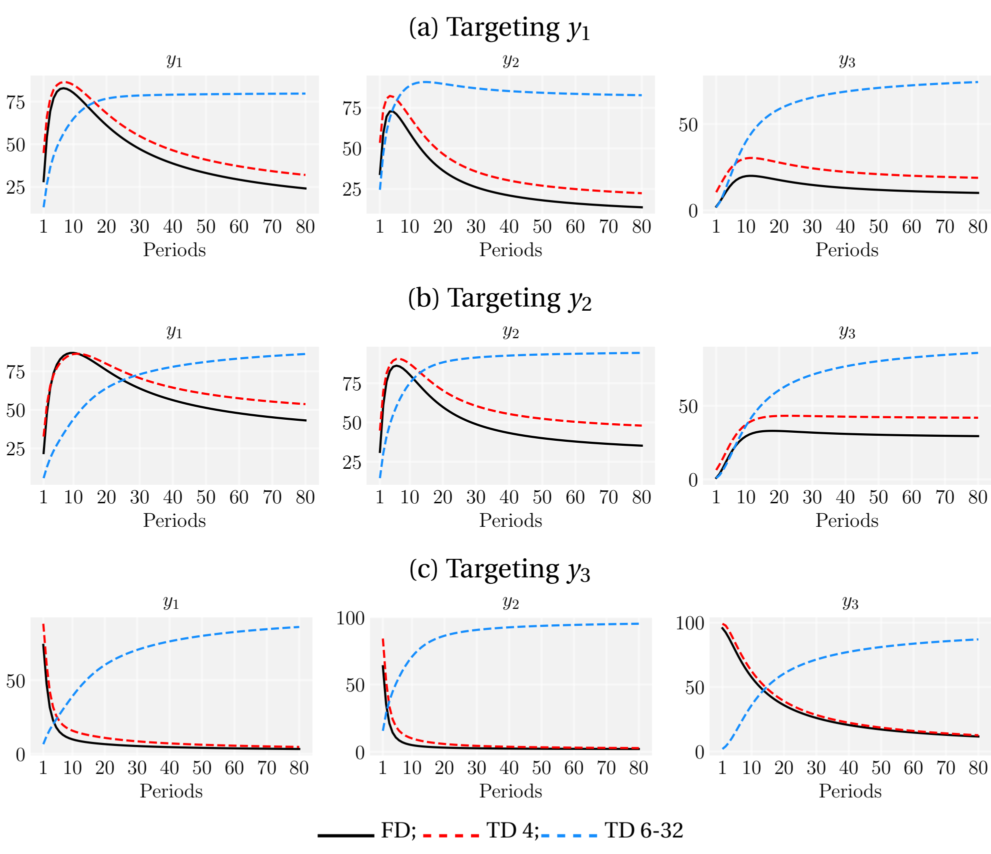


Figure 14: FEV of Identified Shocks



E.2 Time Domain vs Frequency Domain: Empirical Counterpart

We now illustrate how the lessons of the preceding controlled experiment apply to the actual data, too. Figure 15 and Table 16 compare the properties of our MBC shock, which is identified by target the 6-32 quarter band in the frequency domain (FD), to two time-domain (TD) alternatives, the shock that targets the 6-32 quarter horizon range and the shock that targets the 4 quarter horizon. Clearly, the picture seen in the data is the same as that seen in our controlled experiment.

Figure 1 in the main text and Figure 12 in Online Appendix D paint a complementary picture in terms of the TD properties of our FD-identified MBC shock: its IRFs and FEV contributions peak within 1 to 4 quarters. Together, these results clarify the following point: in the actual data, as in the preceding controlled experiment, targeting the business-cycle frequencies in the frequency domain is essentially the same as targeting a horizon of about a year in the time domain.

Figure 15: Frequency-Domain vs Time-Domain Identification (IRFs)

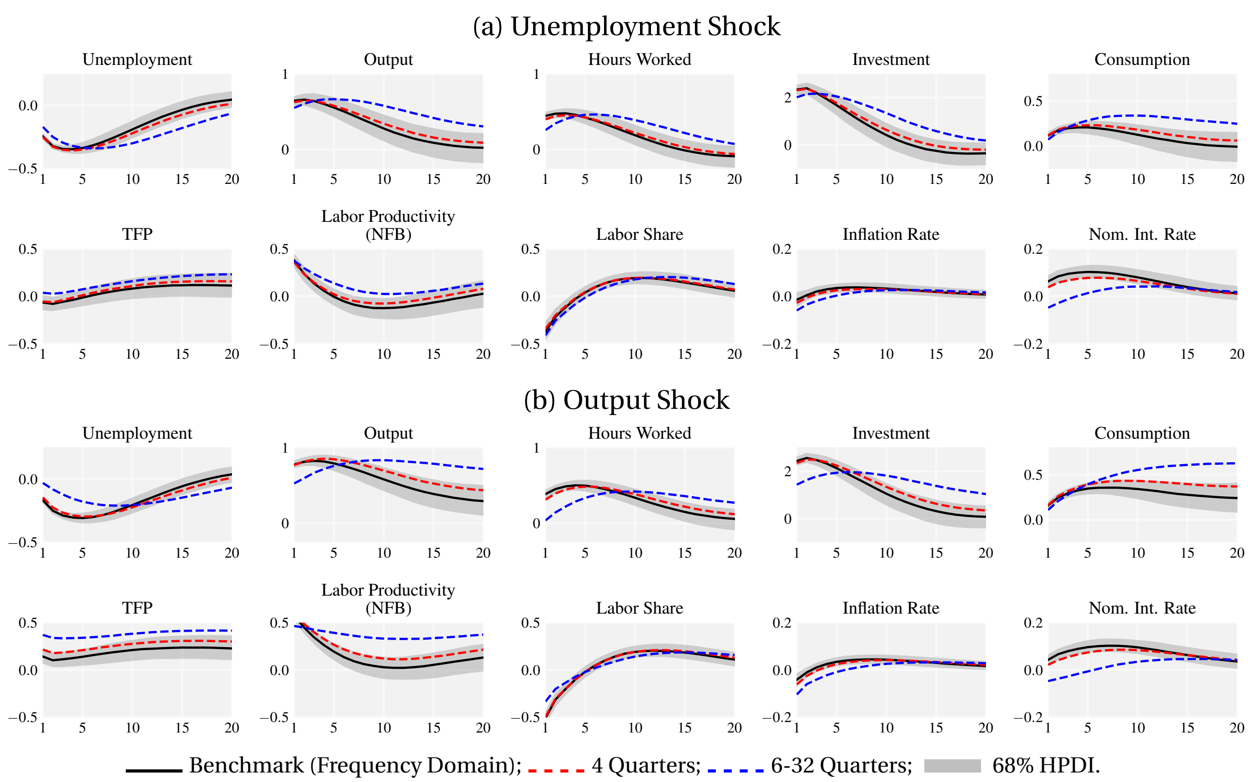


Figure 16: Frequency-Domain vs Time-Domain Identification (FEV)

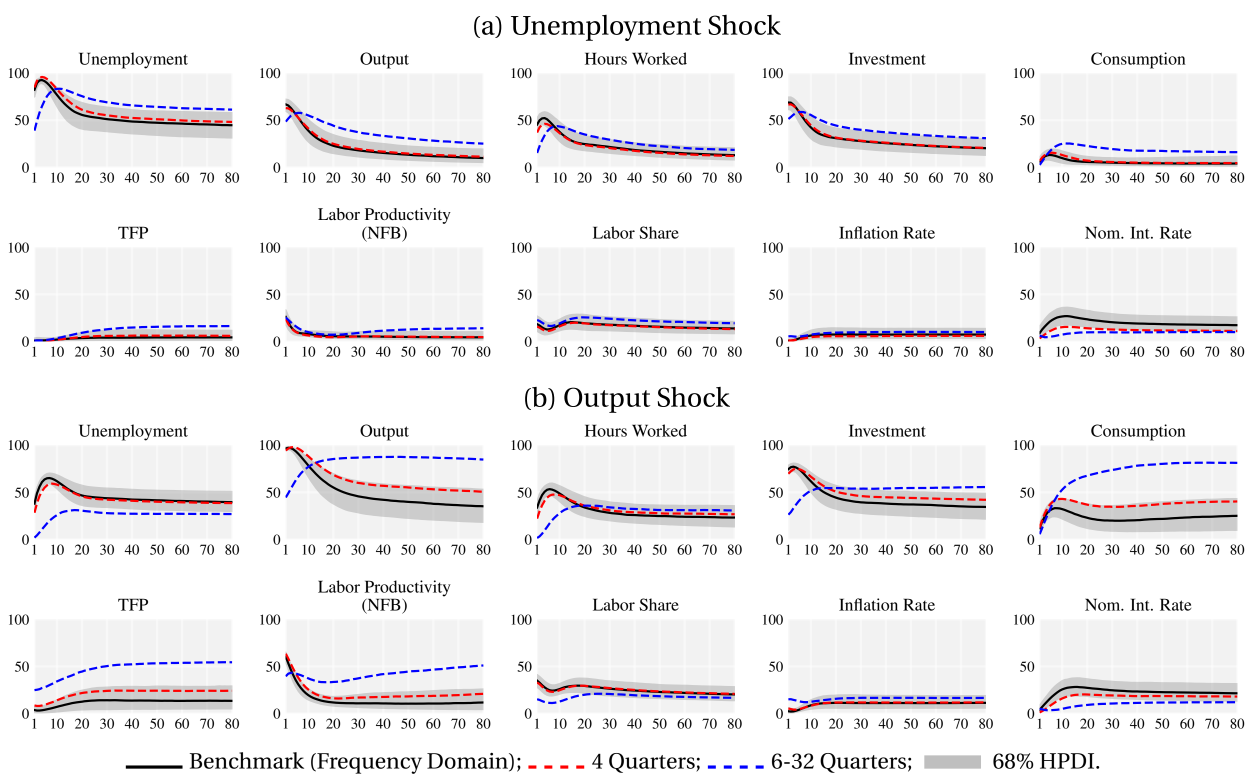


Table 16: Frequency-Domain vs Time-Domain Identification (Variance Contributions)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
Unemployment Shock										
Benchmark	73.71	58.51	47.72	62.09	20.38	5.86	23.91	27.02	6.96	22.27
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]	[2.44,10.96]	[17.27,31.22]	[18.39,35.93]	[3.24,12.28]	[14.22,30.97]
4 Qrts	71.18	53.14	41.02	57.29	19.43	5.14	19.40	24.43	5.62	12.80
	[62.71,77.79]	[46.19,59.10]	[33.52,47.92]	[50.43,63.96]	[13.25,26.17]	[2.15, 9.59]	[14.14,25.08]	[18.27,30.77]	[2.59, 9.95]	[7.50,19.49]
6-32 Qrts	54.75	48.70	35.45	49.93	22.76	3.76	20.31	31.04	11.06	11.59
	[35.77,68.36]	[31.38,61.30]	[22.85,46.95]	[32.38,64.71]	[15.51,30.93]	[1.40, 7.81]	[11.75,29.92]	[17.61,41.56]	[5.35,19.15]	[5.44,22.85]
Output Shock										
Benchmark	56.24	80.13	44.73	67.13	33.03	4.24	41.31	40.20	10.47	16.89
	[48.94,61.93]	[72.80,86.44]	[37.36,51.68]	[60.72,72.82]	[25.04,40.44]	[1.76, 8.32]	[35.29,47.43]	[32.75,47.40]	[5.97,16.75]	[11.00,26.08]
4 Qrts	47.35	77.31	36.58	61.44	34.87	6.73	40.73	38.00	11.84	10.59
	[39.89,53.93]	[68.65,84.43]	[29.28,44.34]	[54.05,68.39]	[27.06,42.04]	[3.28,11.52]	[34.40,46.94]	[31.73,44.45]	[7.51,17.55]	[6.13,16.46]
6-32 Qrts	18.27	43.46	18.64	29.04	29.67	18.45	29.64	19.09	20.25	8.93
	[10.61,27.39]	[28.60,58.93]	[11.50,26.41]	[17.85,42.03]	[20.91,40.11]	[9.34,30.52]	[20.10,39.94]	[8.61,29.96]	[12.15,30.52]	[3.37,17.88]

Note: The two parts of the table correspond to different targeted variables, unemployment or GDP. In each part, the first row correspond to our benchmark, frequency-domain identification of the shock, while the other rows correspond to time-domain identification. In particular, three cases are reported, depending on whether the shock is constructed by maximizing its contribution to the FEV of the respective variable at horizons of 4 quarters and 6 to 32 quarters. The columns report the contributions of the thus-identified shocks to the business-cycle volatilities of all the variables.

Table 17: Frequency-Domain vs Time-Domain Identification (Long-run Variance Contributions)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
Unemployment Shock										
Benchmark	20.83	4.64	5.45	5.16	4.13	4.09	3.88	3.12	5.77	9.12
	[8.37,38.94]	[0.52,15.85]	[1.25,15.40]	[0.79,16.81]	[0.38,14.93]	[0.41,14.48]	[0.37,14.19]	[0.78,10.16]	[1.70,13.54]	[2.68,20.00]
4 Qrts	28.98	5.60	5.21	6.12	5.02	4.98	4.71	3.75	5.48	6.11
	[15.64,44.94]	[0.61,16.35]	[1.37,13.98]	[1.04,16.67]	[0.52,14.99]	[0.66,15.96]	[0.54,14.95]	[0.93,11.59]	[1.70,13.15]	[1.85,14.89]
6-32 Qrts	59.26	15.34	11.27	16.05	14.27	15.97	15.25	12.50	9.58	9.84
	[36.87,75.29]	[2.86,36.91]	[2.75,29.82]	[3.72,36.47]	[2.43,36.08]	[3.17,37.18]	[2.97,36.14]	[3.63,33.38]	[3.03,24.80]	[2.30,29.04]
Output Shock										
Benchmark	24.84	27.40	14.90	24.98	26.13	24.67	25.32	16.83	10.36	11.51
	[11.28,40.55]	[9.10,47.47]	[3.06,34.28]	[7.45,46.00]	[8.80,46.67]	[7.44,44.59]	[7.88,45.44]	[4.03,35.26]	[3.74,20.80]	[4.44,23.66]
4 Qrts	30.35	40.21	18.66	36.97	39.39	38.13	39.86	29.51	12.17	11.84
	[16.25,45.66]	[19.91,59.26]	[3.74,42.75]	[16.32,57.54]	[18.86,58.40]	[19.00,56.40]	[19.59,57.12]	[10.65,47.67]	[4.80,24.40]	[4.64,24.94]
6-32 Qrts	31.88	72.00	23.42	65.23	72.35	73.65	75.60	62.74	17.85	20.46
	[16.20,54.05]	[41.15,90.33]	[5.14,57.75]	[31.74,88.65]	[43.05,89.94]	[49.50,88.74]	[51.58,89.96]	[34.74,79.80]	[7.03,36.79]	[8.51,44.54]

Note: The two parts of the table correspond to different targeted variables, unemployment or GDP. In each part, the first row correspond to our benchmark, frequency-domain identification of the shock, while the other rows correspond to time-domain identification. In particular, three cases are reported, depending on whether the shock is constructed by maximizing its contribution to the FEV of the respective variable at horizons of 4 quarters and 6 to 32 quarters. The columns report the contributions of the thus-identified shocks to the business-cycle volatilities of all the variables.

F Long Run PCA

Table 7 in Section 4.1 reported the first principal component over the business-cycle frequencies (the band corresponding to $6-32$ quarters). For completeness, Table 18 here reports the corresponding object over the long-run frequencies (the band corresponding to $80-\infty$ quarters). The picture that emerges corroborates the existence of a single unit-root force driving almost the entirety of the long-run fluctuations in TFP and the key macroeconomic quantities.

Table 18: First Principal Component, Long Term, 1955-2017

	u	Y	h	I	C	π	R	r	TFP	Y/h	w	wh/Y
Raw Data	10.43	99.93	64.93	98.11	99.66	6.20	6.97	2.44	98.33	99.32	99.74	73.89
VAR-Based	12.20	97.88	5.82	95.08	96.32	3.94	6.66	9.99	88.97	98.18	96.59	32.74
Normalized Data	10.38	99.18	62.59	95.57	99.83	9.85	10.33	3.52	96.69	98.96	98.72	78.28
VAR Normalized	29.44	90.64	17.49	86.44	89.46	11.89	20.37	19.00	88.36	89.67	94.16	49.18

G Robustness of Empirical Findings

In Section 4.3, we established the robustness of the empirical properties of the shock that targets unemployment across elevent specifications. In the first subsection of this appendix, we first show that the same robustness property characterizes the other shocks that form our anatomy. In the next two subsections, we expand on some additional findings from the two extended VARs that show up as rows 9 and 10 in these tables. In the last two subsections, we finally fill in a few details regarding the VECM specifications and measurement of the relative prices of investment.

G.1 Beyond the unemployment shock: other elements of the anatomy

Table 8 in the main text reported the variance contributions of the shock that targets unemployment across eleven specifications. Table 19 through Table 23 here repeat the exercise of a select subset of the other elements comprising our anatomy: the shocks that target GDP, hours, investment, and inflation. Although omitted here for the shake of saving space, the same robustness property is also present in terms of IRFs.

Table 19: The MBC Shock, Targeting Unemployment, Variance Contributions (6-32 Quarters)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
[1] Benchmark	73.71	58.51	47.72	62.09	20.38	5.86	23.91	27.02	6.96	22.27
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]	[2.44,10.96]	[17.27,31.22]	[18.39,35.93]	[3.24,12.28]	[14.22,30.97]
[2] 4 lags	74.49	58.23	49.16	62.42	21.20	6.28	23.10	27.87	6.91	24.75
	[67.98,80.77]	[50.51,65.05]	[42.24,56.10]	[55.15,69.04]	[14.13,28.78]	[2.82,11.74]	[16.83,31.02]	[18.93,37.34]	[3.23,12.15]	[16.20,33.77]
[3] VECM(1)	62.43	50.27	48.81	53.39	34.88	18.13	23.80	24.11	10.46	33.37
	[56.47,68.44]	[43.46,57.44]	[42.14,55.91]	[47.05,60.01]	[26.27,44.47]	[9.03,29.45]	[17.14,32.73]	[16.36,34.17]	[4.39,20.13]	[19.07,48.60]
[4] VECM(2)	64.85	54.99	48.82	53.78	44.93	12.17	19.51	29.71	11.29	19.51
	[57.60,71.25]	[46.53,62.59]	[42.52,55.66]	[46.37,60.86]	[33.73,55.68]	[6.00,19.88]	[13.11,27.14]	[20.04,39.49]	[5.09,19.32]	[10.94,32.92]
[5] 1948-2017	78.98	65.32	49.61	63.76	19.52	6.14	26.53	29.62	5.16	16.94
	[72.86,84.10]	[59.25,71.33]	[43.55,55.83]	[57.87,70.19]	[13.70,26.91]	[2.51,11.05]	[19.68,33.57]	[22.10,37.53]	[2.28,10.00]	[10.37,24.31]
[6] 1960-2007	68.15	59.93	55.99	65.02	20.67	6.02	25.04	29.96	10.70	27.03
	[61.82,73.98]	[48.14,68.85]	[47.10,63.10]	[55.39,72.59]	[13.52,31.01]	[2.24,13.76]	[16.29,36.15]	[19.57,43.29]	[5.49,18.89]	[16.86,37.53]
[7] pre-Volcker	74.23	56.75	43.21	61.50	23.43	6.82	30.69	28.43	17.45	27.60
	[64.05,82.35]	[45.87,66.62]	[32.38,53.49]	[51.63,70.37]	[13.58,35.24]	[2.45,15.11]	[20.09,42.11]	[16.92,42.01]	[9.39,28.74]	[16.81,40.08]
[8] post-Volcker	73.39	50.37	50.65	58.44	20.23	7.94	18.46	23.01	4.65	15.05
	[65.47,80.53]	[41.45,58.81]	[42.60,59.01]	[50.17,66.23]	[12.46,28.65]	[3.67,14.49]	[11.61,26.94]	[14.23,33.51]	[1.74,10.06]	[7.48,25.22]
[9] Extended	59.33	50.61	45.50	52.91	21.83	4.81	26.69	27.82	12.12	28.99
	[53.73,65.69]	[43.05,57.99]	[39.71,51.26]	[44.97,60.17]	[14.87,31.14]	[1.95,10.39]	[19.36,34.75]	[14.05,44.15]	[6.57,19.70]	[17.38,42.75]
[10] Financial	68.57	57.56	46.84	59.95	25.94	7.04	27.20	26.86	8.42	26.59
	[62.38,74.87]	[49.74,64.87]	[39.39,54.03]	[52.26,66.82]	[17.80,34.98]	[3.10,12.97]	[19.45,35.96]	[18.53,37.07]	[3.77,14.98]	[16.82,36.24]
[11] Chained-Type C&I	81.41	59.04	45.96	61.52	17.36	4.03	20.35	20.19	5.82	23.17
	[75.30,86.36]	[52.45,64.82]	[39.33,52.36]	[54.39,67.49]	[12.10,23.41]	[1.56, 7.51]	[14.80,26.64]	[13.97,26.72]	[2.62,10.41]	[16.31,30.38]

Table 20: The MBC Shock, Targeting Output, Variance Contributions (6-32 Quarters)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
[1] Benchmark	56.24	80.13	44.73	67.13	33.03	4.24	41.31	40.20	10.47	16.89
	[48.94,61.93]	[72.80,86.44]	[37.36,51.68]	[60.72,72.82]	[25.04,40.44]	[1.76, 8.32]	[35.29,47.43]	[32.75,47.40]	[5.97,16.75]	[11.00,26.08]
[2] 4 lags	56.48	79.38	44.56	67.35	33.20	5.49	40.56	41.06	11.35	17.71
	[50.18,63.14]	[71.95,85.64]	[37.14,52.69]	[61.08,73.31]	[26.42,40.63]	[2.44,10.40]	[34.22,46.76]	[33.38,48.23]	[6.31,17.09]	[9.90,26.49]
[3] VECM(1)	51.21	62.37	43.05	54.74	44.17	9.71	30.54	35.49	9.37	21.55
	[43.96,57.68]	[56.11,69.41]	[35.30,50.83]	[48.66,61.51]	[36.00,54.01]	[5.27,17.85]	[24.50,37.65]	[26.32,44.21]	[4.40,17.63]	[9.85,39.01]
[4] VECM(2)	52.31	68.59	43.52	55.54	56.07	7.65	33.22	37.57	9.14	15.80
	[45.04,59.90]	[60.91,76.13]	[36.30,50.88]	[48.61,62.06]	[46.24,64.66]	[4.38,12.83]	[26.99,40.03]	[29.75,45.14]	[3.75,16.24]	[8.90,25.36]
[5] 1948-2017	62.00	86.39	52.46	70.81	34.79	3.17	43.83	41.02	5.32	14.96
	[56.59,67.36]	[80.69,91.04]	[46.51,58.63]	[65.86,75.73]	[27.48,42.14]	[1.37, 6.49]	[38.37,49.88]	[34.62,47.68]	[2.49, 9.78]	[9.05,22.02]
[6] 1960-2007	55.40	78.24	48.87	70.64	36.65	15.65	44.61	42.96	12.49	16.21
	[48.07,62.00]	[71.45,84.76]	[41.66,56.51]	[64.26,75.98]	[27.53,44.92]	[8.55,24.41]	[37.30,52.12]	[35.77,50.99]	[6.78,20.65]	[8.36,25.16]
[7] pre-Volcker	60.57	71.01	45.61	61.91	39.59	5.58	45.38	43.92	19.53	23.52
	[50.61,68.94]	[61.45,80.34]	[34.80,56.13]	[51.71,70.91]	[28.04,50.75]	[2.11,14.16]	[36.13,55.02]	[32.53,54.58]	[11.25,30.88]	[13.15,37.61]
[8] post-Volcker	46.34	77.66	40.88	66.18	35.62	7.63	26.34	27.27	3.59	17.45
	[37.67,54.73]	[68.56,84.52]	[32.34,50.00]	[57.96,73.11]	[25.20,45.83]	[3.30,14.45]	[19.91,33.98]	[19.66,35.55]	[1.36, 8.36]	[8.49,27.94]
[9] Extended	47.56	65.28	40.18	56.71	31.43	4.73	40.33	42.69	10.89	17.55
	[41.35,54.06]	[58.72,72.44]	[33.19,46.69]	[50.57,63.11]	[24.19,38.98]	[2.11, 9.17]	[33.83,46.75]	[33.03,51.32]	[6.26,17.07]	[9.74,28.63]
[10] Financial	53.90	75.33	43.57	62.44	35.42	5.19	41.43	38.42	11.54	19.98
	[47.10,60.67]	[68.02,82.18]	[36.40,50.77]	[55.85,68.60]	[27.88,43.94]	[2.82, 9.31]	[34.82,47.79]	[31.20,45.65]	[6.56,17.79]	[12.54,29.42]
[11] Chained-type C&I	57.80	85.61	43.46	69.68	32.40	2.76	39.00	31.36	8.85	18.31
	[51.26,63.00]	[79.50,90.50]	[36.44,50.46]	[64.03,74.42]	[25.23,40.53]	[1.43, 5.07]	[33.69,45.44]	[24.98,37.66]	[4.82,14.15]	[11.45,26.07]

Table 21: The MBC Shock, Targeting Hours Worked, Variance Contributions (6-32 Quarters)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
[1] Benchmark	49.84	47.54	70.45	47.99	21.78	11.62	22.61	19.47	7.23	22.38
	[42.43,56.53]	[38.20,55.67]	[64.25,77.04]	[38.49,55.96]	[15.30,29.22]	[6.14,18.14]	[15.58,29.66]	[11.73,29.24]	[3.32,13.31]	[15.09,31.87]
[2] 4 lags	51.82	46.53	70.17	45.99	23.11	10.22	19.54	19.25	6.80	24.55
	[44.30,58.55]	[37.75,56.07]	[63.67,76.61]	[36.73,54.81]	[16.46,30.73]	[5.22,18.05]	[13.51,26.97]	[10.70,28.70]	[3.25,11.93]	[15.81,33.91]
[3] VECM(1)	52.16	46.09	58.32	48.52	32.81	28.64	23.63	18.58	13.87	39.95
	[45.43,58.79]	[38.60,54.00]	[53.32,63.44]	[41.43,55.97]	[23.69,43.81]	[15.87,40.14]	[16.48,32.70]	[11.07,29.94]	[5.96,25.56]	[25.71,53.96]
[4] VECM(2)	53.91	50.41	57.82	49.65	41.91	16.99	18.34	25.72	10.93	23.69
	[45.99,61.44]	[39.92,59.50]	[52.81,62.97]	[41.34,57.77]	[26.35,55.14]	[7.95,28.24]	[11.83,26.80]	[13.88,40.00]	[4.98,18.61]	[12.51,44.29]
[5] 1948-2017	51.98	57.31	76.44	56.45	23.48	8.49	23.93	25.26	7.85	16.43
	[45.78,57.75]	[50.34,63.96]	[70.91,81.81]	[48.96,63.94]	[16.93,30.48]	[4.35,14.47]	[17.81,30.80]	[17.60,34.06]	[4.09,13.28]	[10.29,23.33]
[6] 1960-2007	53.21	50.95	70.91	52.51	21.39	5.83	18.52	26.91	7.75	18.67
	[46.03,60.23]	[42.71,59.85]	[63.83,77.35]	[44.58,60.62]	[13.62,30.77]	[2.43,10.92]	[11.48,27.04]	[17.88,37.23]	[3.22,15.89]	[10.74,29.52]
[7] pre-Volcker	45.56	47.14	67.93	50.35	23.45	19.40	27.09	21.50	17.76	24.53
	[33.61,56.43]	[36.05,58.16]	[58.71,76.98]	[37.67,61.28]	[14.49,35.17]	[9.36,30.19]	[17.01,39.19]	[11.24,35.79]	[10.48,29.26]	[13.88,40.91]
[8] post-Volcker	50.25	44.09	72.21	44.75	19.96	6.93	16.02	14.80	3.61	13.01
	[42.13,58.72]	[35.21,53.20]	[63.07,80.11]	[35.54,54.40]	[12.81,28.05]	[2.91,13.12]	[9.41,23.70]	[8.02,24.30]	[1.32, 8.35]	[5.95,22.97]
[9] Extended	43.09	41.15	61.33	43.02	23.81	10.31	22.64	14.07	12.55	26.84
	[36.17,49.37]	[33.92,48.68]	[55.15,67.24]	[35.24,50.56]	[17.36,31.14]	[4.86,17.26]	[16.06,29.80]	[7.21,24.92]	[7.13,19.79]	[17.00,38.82]
[10] Financial	50.45	49.94	63.65	50.13	27.20	11.29	25.81	22.27	8.77	26.53
	[42.91,57.94]	[39.97,58.12]	[57.66,69.85]	[39.73,59.48]	[18.83,36.31]	[5.35,18.69]	[17.25,35.19]	[12.36,34.58]	[4.29,16.04]	[17.47,35.91]
[11] Chained-type C&I	48.43	46.76	78.87	46.11	20.37	10.92	19.51	13.41	5.76	20.27
	[41.28,54.30]	[39.48,53.30]	[72.70,85.02]	[38.74,52.65]	[14.80,26.59]	[6.25,16.74]	[14.11,26.13]	[7.98,20.55]	[2.67,10.49]	[13.40,27.48]

Table 22: The MBC Shock, Targeting Investment, Variance Contributions (6-32 Quarters)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
[1] Benchmark	59.03	66.60	45.20	80.29	19.01	3.81	33.74	36.44	7.69	21.51
	[51.73,64.55]	[60.40,72.21]	[37.93,51.98]	[72.82,86.97]	[12.27,27.34]	[1.38, 7.83]	[27.72,40.30]	[29.21,44.21]	[3.65,12.96]	[13.91,30.28]
[2] 4 lags	59.99	66.75	43.60	79.98	20.51	5.22	32.41	37.29	7.29	21.25
	[53.25,66.00]	[60.22,72.56]	[36.01,51.36]	[72.18,86.39]	[13.93,28.34]	[1.99,10.09]	[26.04,39.20]	[29.53,44.75]	[3.68,12.94]	[13.48,30.63]
[3] VECM(1)	54.47	55.01	45.49	61.58	34.54	12.29	26.98	32.02	9.54	29.65
	[47.86,60.60]	[48.96,61.65]	[38.05,53.16]	[55.78,68.31]	[25.35,45.08]	[5.84,22.09]	[20.34,34.17]	[22.71,41.00]	[4.00,18.54]	[16.48,45.86]
[4] VECM(2)	55.79	60.32	46.08	63.02	44.57	8.59	27.15	37.96	9.59	20.51
	[49.03,62.87]	[53.38,67.58]	[39.48,53.54]	[56.30,69.67]	[32.28,55.14]	[4.23,15.06]	[20.32,34.38]	[28.53,46.61]	[3.90,17.23]	[11.51,33.76]
[5] 1948-2017	61.66	72.01	53.31	85.20	21.44	2.98	36.88	36.80	7.46	18.81
	[56.29,67.03]	[67.21,76.62]	[46.78,59.21]	[79.20,90.07]	[14.54,29.61]	[1.19, 6.60]	[30.74,43.40]	[30.54,43.51]	[3.92,13.31]	[12.01,26.03]
[6] 1960-2007	56.94	67.79	48.22	81.22	23.69	11.53	36.28	37.39	11.20	22.37
	[50.22,63.46]	[60.98,73.81]	[40.67,55.65]	[74.33,87.11]	[15.10,32.48]	[5.03,20.50]	[28.74,43.88]	[29.88,45.86]	[5.71,19.37]	[13.64,31.05]
[7] pre-Volcker	62.79	60.25	48.49	72.75	24.92	7.25	36.32	32.97	17.94	29.75
	[53.55,70.93]	[49.47,69.59]	[37.33,58.33]	[62.21,81.58]	[13.48,37.86]	[2.49,15.90]	[25.65,47.21]	[21.26,45.81]	[9.66,29.65]	[17.67,44.22]
[8] post-Volcker	51.27	62.59	40.40	82.79	21.88	5.89	19.01	25.19	3.72	17.72
	[42.22,59.14]	[54.28,69.59]	[31.31,49.31]	[73.94,89.33]	[14.03,31.04]	[2.18,11.48]	[13.31,26.96]	[17.22,33.15]	[1.42, 7.89]	[9.66,27.00]
[9] Extended	49.51	56.64	42.79	65.72	20.17	3.91	34.47	41.46	10.87	21.42
	[43.52,55.92]	[50.63,62.73]	[35.92,48.65]	[58.67,72.73]	[13.41,27.74]	[1.54, 8.04]	[28.44,41.41]	[31.04,50.82]	[6.03,16.56]	[12.92,32.65]
[10] Financial	57.04	63.64	44.94	74.05	23.94	4.92	35.15	35.00	8.54	24.44
	[50.63,63.29]	[57.22,69.74]	[37.75,52.18]	[66.67,80.32]	[15.73,32.62]	[2.40, 9.55]	[28.22,41.96]	[27.81,42.40]	[4.11,14.77]	[16.05,33.52]
[11] Chained-type C&I	59.34	69.12	42.24	86.02	18.43	2.42	31.03	27.74	6.49	22.05
	[53.12,64.87]	[63.69,74.05]	[34.89,49.01]	[79.25,90.69]	[12.48,25.84]	[0.93, 4.86]	[25.76,37.27]	[21.75,34.11]	[3.22,11.60]	[15.23,29.99]

Table 23: The Inflation Shock, Variance Contributions (6-32 Quarters)

	u	Y	h	I	C	TFP	Y/h	Wh/Y	π	R
[1] Benchmark	4.24	7.88	3.32	3.01	15.14	3.55	7.37	1.96	83.03	7.61
	[1.62, 8.20]	[3.77,12.87]	[1.21, 6.92]	[1.12, 6.60]	[10.00,21.93]	[1.75, 7.08]	[4.11,12.31]	[0.66, 4.60]	[76.11,88.46]	[3.36,14.61]
[2] 4 lags	5.08	9.21	3.87	3.49	15.77	3.70	9.85	2.30	82.22	6.89
	[2.14, 9.53]	[4.82,15.07]	[1.49, 8.12]	[1.18, 7.46]	[10.29,22.23]	[1.89, 6.83]	[5.48,15.73]	[0.81, 5.66]	[76.14,87.42]	[2.84,13.13]
[3] VECM(1)	11.81	14.22	11.98	9.92	21.13	12.05	17.10	6.59	86.63	18.65
	[5.47,19.24]	[7.93,22.41]	[5.34,19.78]	[4.24,16.89]	[12.53,30.13]	[6.91,18.10]	[9.85,24.32]	[2.74,12.27]	[80.27,91.16]	[10.45,27.75]
[4] VECM(2)	4.03	2.00	4.46	3.11	1.84	11.15	3.37	4.22	85.90	5.17
	[1.31, 8.55]	[0.64, 5.43]	[1.77, 8.71]	[1.05, 7.13]	[0.47, 5.11]	[6.55,16.98]	[1.34, 7.04]	[2.01, 7.65]	[78.72,91.04]	[2.38, 9.46]
[5] 1948-2017	2.71	2.53	4.60	5.90	12.50	7.25	6.62	2.03	86.62	6.52
	[0.95, 5.85]	[0.88, 5.31]	[2.00, 7.99]	[3.24, 9.79]	[7.19,19.13]	[3.47,12.15]	[3.57,10.92]	[0.65, 4.87]	[81.29,90.86]	[2.54,12.23]
[6] 1960-2007	8.86	8.93	10.01	5.84	19.06	3.47	10.74	4.70	80.78	11.71
	[4.33,15.49]	[4.25,16.27]	[4.63,17.43]	[2.52,11.75]	[12.21,27.47]	[1.68, 7.16]	[5.63,17.61]	[1.95, 9.68]	[73.48,86.89]	[5.21,20.70]
[7] pre-Volcker	10.46	14.57	6.81	11.29	21.23	12.30	17.25	8.99	66.39	9.26
	[3.59,22.60]	[6.74,27.14]	[2.18,17.67]	[4.00,22.56]	[12.76,32.51]	[5.03,24.28]	[9.03,28.81]	[3.32,20.32]	[55.30,77.59]	[3.22,23.14]
[8] post-Volcker	6.76	9.02	7.02	5.40	14.74	2.34	7.96	2.51	87.67	22.97
	[2.78,13.21]	[4.46,16.22]	[2.70,13.10]	[2.18,10.68]	[8.25,23.75]	[0.85, 6.05]	[3.50,14.84]	[0.95, 5.88]	[81.23,92.33]	[12.99,33.79]
[9] Extended	8.24	9.45	7.13	5.22	14.13	5.30	11.37	3.68	75.28	13.59
	[3.68,14.72]	[4.90,15.69]	[3.06,13.46]	[1.95,10.61]	[8.24,21.01]	[2.67, 9.34]	[6.50,17.81]	[1.43, 8.28]	[67.59,81.92]	[7.09,22.06]
[10] Financial	4.85	7.93	3.88	3.69	14.06	3.92	7.89	2.07	80.61	8.49
	[2.03, 9.37]	[3.94,13.34]	[1.46, 8.31]	[1.32, 7.50]	[8.20,20.25]	[1.88, 7.15]	[4.36,12.52]	[0.83, 4.70]	[73.22,86.65]	[3.55,15.36]
[11] Chained type C&I	1.88	4.64	1.54	2.11	6.80	3.23	6.25	1.75	80.18	6.92
	[0.57, 5.11]	[1.86, 9.17]	[0.56, 3.91]	[0.68, 4.69]	[3.03,11.99]	[1.41, 6.36]	[2.97,10.39]	[0.64, 3.88]	[73.40,85.71]	[2.40,13.24]

G.2 Stock Prices, Relative Price of Investment, and Utilization

Here, we describe additional properties of the specification in row 9 ("Extended") of Tables 8 and 20-23. Recall that this specification contains three additional variables: stock prices (SP); the relative price of investment (P_i/P_c); and capital utilization (z). Our measure of stock prices is in real terms, is the same as that used by Beaudry and Portier, and is taken from Robert Shiller's website (`http://www.econ.yale.edu/~shiller/data/ie_data.xls`). The relative price of investment is the ratio of the price of Gross Private Domestic Investment and Durables to the price of Non Durables and Services; its computation is detailed in Online Appendix G.5. Finally the capacity utilization rate variable corresponds to the Capacity Utilization in Manufacturing (SIC), `CUMFNS` in the Federal Reserve Economic Database.

The inclusion of stock prices and the relative price of investment is motivated by works that uses these variable in the identification of, respectively news shocks and investment-specific technology shocks. The inclusion of capacity utilization, on the other hand, helps shed light on why labor productivity moves with the MBC shock while TFP does not. Last but not least, the inclusion of all three variables at once helps illustrate the robustness of our main findings to the addition of more information—a point already made in Tables 8 and 20-23.

Here, Tables 24-25 and Figure 17 complete the picture by reporting the contribution of the MBC shock to the short-run and long-run volatility of the aforementioned three variables, as well as the properties of the shock that targets the business-cycle volatility of stock prices.[44] The most noteworthy new findings are the following.

First, the disconnect between the business cycle and technology applies to both TFP and investment-specific technology, as measured by the relative price of investment. For instance, the MBC shock explains less than 5% of the volatility of either of these variables at either the business-cycle or the long-run frequencies.

Second, the shock that targets Stock Prices accounts for 21 to 24% of the business-cycle volatility in unemployment, output and investment, and 15 to 22% of the long-run volatility in TFP, output and investment. In this regard, the fluctuations in stock prices appear to be disconnected from current technology and to contain non-trivial statistical information about both the business cycle and the long-term prospects of the economy. The extent to which these patterns reflect the presence of a news shock is explored further in Appendix C.

Finally, the shock that targets utilization at the business-cycle frequencies is similar to the MBC shock

[44]The shocks that target business cycle volatility in TFP and the relative price of investment lack novelty as they contribute negligibly to the volatility of the macroeconomic quantities.

in terms of both variance contributions and IRFs (Figure 17). This helps understand why labor productivity increases in response to the MBC shock, while TFP does not move.

Table 24: Extended VAR, Business Cycle Variance Contributions

	u	Y	h	I	C	z	TFP	Y/h
MBC shock	59.33	50.61	45.50	52.91	21.83	51.71	4.81	26.69
	[53.73,65.69]	[43.05,57.99]	[39.71,51.26]	[44.97,60.17]	[14.87,31.14]	[45.55,57.66]	[1.95,10.39]	[19.36,34.75]
SP shock	24.14	23.05	15.75	21.65	24.63	18.10	4.37	10.81
	[18.31,31.23]	[16.99,29.55]	[10.45,22.24]	[15.75,28.29]	[18.47,31.05]	[12.64,24.36]	[2.46, 7.30]	[6.55,16.04]
	P_i/P_c	SP	wh/Y	π	R	GDP/h	w	r
MBC shock	4.42	11.54	27.82	12.12	28.99	10.70	4.48	12.52
	[1.69, 9.62]	[5.16,22.75]	[14.05,44.15]	[6.57,19.70]	[17.38,42.75]	[5.36,19.24]	[1.93,10.10]	[5.56,21.67]
SP shock	3.39	82.82	11.29	9.27	5.48	12.39	13.19	2.40
	[1.32, 7.33]	[76.59,87.93]	[6.25,17.22]	[4.28,14.73]	[2.40,10.26]	[7.59,18.64]	[7.93,19.43]	[0.87, 5.04]

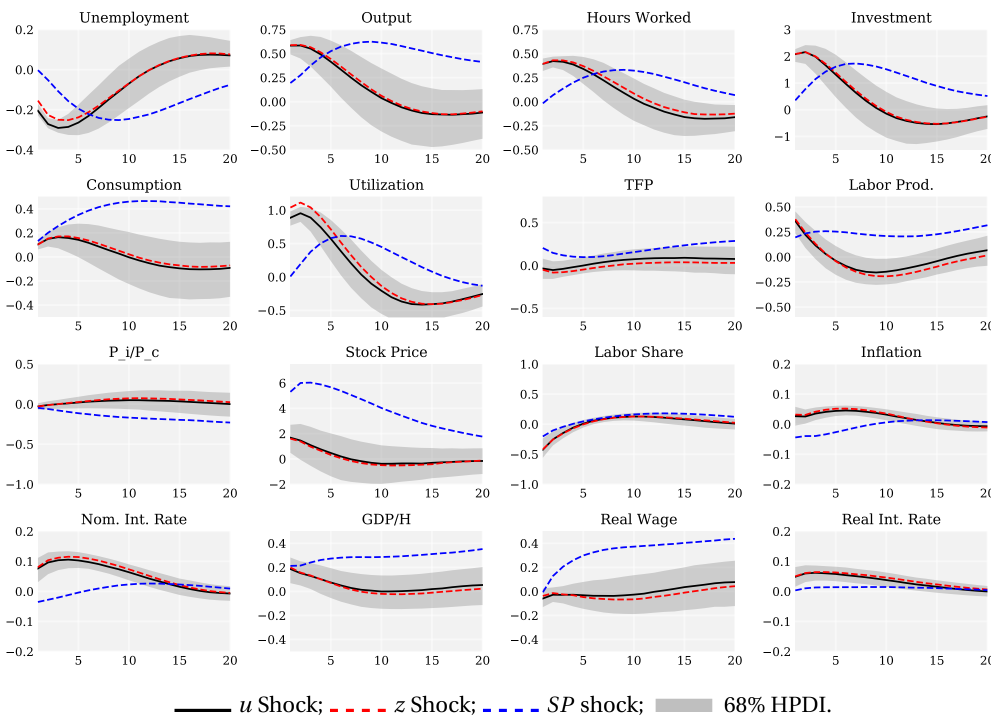
Note: The rows correspond to the shocks targeting business-cycle variation in unemployment (MBC shock) and Stock Prices (SP shock), respectively. The columns correspond to the 13 variables in the VAR. These are the 10 variables from our baseline specification, and also capacity utilization z, the Relative Price of Investment P_i/P_c and stock prices SP.

Table 25: Extended VAR, Long-Run Variance Contributions (80-∞ Quarters)

	u	Y	h	I	C	z	TFP	Y/h
MBC shock	9.49	4.52	3.96	4.58	4.43	6.36	4.39	4.59
	[3.03,24.04]	[0.45,17.60]	[1.11,11.23]	[0.78,18.25]	[0.40,16.92]	[2.19,15.41]	[0.59,17.66]	[0.52,17.40]
SP shock	30.39	14.55	8.95	14.85	14.76	17.35	21.67	21.88
	[14.89,47.64]	[2.96,38.30]	[2.29,25.66]	[3.49,38.37]	[2.87,38.64]	[7.85,32.71]	[5.53,43.52]	[5.59,44.09]
	P_i/P_c	SP	wh/Y	π	R	GDP/h	w	r
u	4.60	5.23	4.36	7.03	11.23	4.55	4.58	8.19
	[0.59,17.02]	[1.13,16.97]	[0.79,14.99]	[2.20,16.45]	[2.88,24.32]	[0.50,17.35]	[0.50,17.62]	[2.05,19.88]
SP	26.99	34.63	24.51	9.16	12.68	20.31	20.96	18.88
	[8.96,46.73]	[16.95,52.70]	[9.89,42.83]	[3.08,21.50]	[3.21,32.22]	[4.72,42.71]	[5.00,43.46]	[6.11,37.94]

Note: The rows correspond to the shocks targeting business-cycle frequencies variation in unemployment (MBC shock) and Stock Prices (SP shock) respectively. The columns correspond to the 13 variables in the VAR. These are the 10 variables from our baseline specification, plus capacity utilization (z), the Relative Price of Investment (P_i/P_c) and stock prices (SP).

Figure 17: Extended VAR, IRFs



G.3 Financial Variables

Here we provide additional information on the VAR that adds the credit spread (CS) and appears as row 10 ("Financial") of Tables 8 and 20-23. We also consider a more comprehensive specification, called "Financial-Full," that contains three additional financial variables at the expense of a shorter sample period. The additional variables are the slope of the term structure (TS), the level of credit to non-financial firms (Cr), and the net worth of such firms (WS).

Our measurement of all these variables follows Christiano, Motto, and Rostagno (2014). The credit spread (CS) is the difference between the interest rate on BAA-rated corporate bonds and the 10 year US government bond rate. The slope of the term structure (TS) is the difference between the 10-year constant maturity US government bond yield and the Federal Funds rate. The level of credit (Cr) is taken from the Flow of Funds of the US Federal Reserve Board. Finally, net worth (WS) is measured by the Dow Jones Wilshire 5000 index.[45] Because this index only starts in 1971 and the measure of credit is only available until 2014, the VAR that contains all four financial variables ("Financial-Full") is estimated for the period running from 1971Q1 to 2014Q4. By contrast, the VAR that contains only the credit spread ("Financial", or row 10 of the aforementioned tables) spans the entire 1955Q1-2017Q4 period.

For the purposes of the model evaluation done in Section 6, we have also considered a third specification, which is obtained by restricting the second specification to 1985Q1-2010Q4. This is the period used in the original estimation of the model in Christiano, Motto, and Rostagno (2014). We refer to this specification as "Financial-CMR."

Figure 18 reports the IRFs of the various facets of the MBC shock obtained from these three specifications. Although there are some differences,[46] the main picture remains the same: the reduced-form shocks obtained by targeting unemployment, hours, output, investment and consumption are highly interchangeable.

Perhaps more interestingly, we can now detect the empirical footprint of the MBC shock on the new, financial variables. In particular, we see that the credit spread spikes on impact, while output and the other key macroeconomic quantities respond with a delay, in a hump-shaped manner. From this perspective, the credit spread leads the business cycle. As discussed in Section 6, this property, which is presumably informative about the real-financial nexus, is unfortunately not captured by the model of

[45]Note that the measure of net worth is a stock-market valuation, which differs from that used in the previous subsection (SP500) because the present specification aims at replicating the data used in CMR, while the previous one followed Beaudry and Portier. In any case, it makes little difference which one of these two measures is used as their business-cycle behavior is nearly identical.

[46]Most notably, consumption appears to more closely connected to the MBC shock in the third specification.

Christiano, Motto, and Rostagno (2014).[47]

[47] Although we have omitted it here, we have also looked at the shock that targets the credit spread itself. This shock is similar to the MBC shock in terms of IRFs (comovements), although less so with regard to variance contributions. Importantly, this shock, too, gives rise to pattern mentioned above, with the credit spread itself moving before the key macroeconomic quantities.

Figure 18: Comparing Business-Cycle Factors

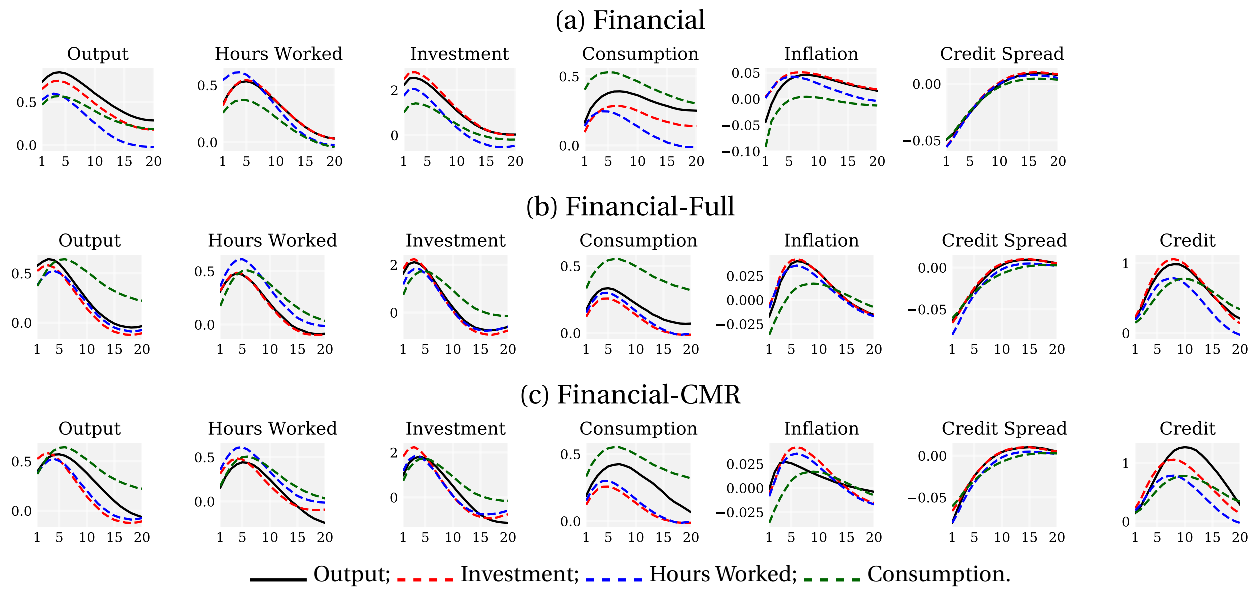


Table 26: Financial VARs, Short-Run Contributions of MBC Shock

	u	Y	h	I	C	π	CS	Cr
Financial	68.57	57.56	46.84	59.95	25.94	8.42	41.56	
	[62.38,74.87]	[49.74,64.87]	[39.39,54.03]	[52.26,66.82]	[17.80,34.98]	[3.77,14.98]	[30.02,54.08]	
Financial-Full	60.47	51.65	53.32	54.63	33.84	13.29	49.68	39.69
	[54.39,67.41]	[43.81,59.37]	[45.45,61.18]	[47.11,62.53]	[22.66,46.48]	[6.12,24.44]	[29.51,62.90]	[28.46,51.23]
Financial-CMR	64.76	53.26	59.60	55.90	35.93	15.83	56.05	46.16
	[56.31,73.66]	[40.61,64.00]	[48.45,69.36]	[45.01,66.30]	[21.80,51.92]	[6.79,30.26]	[36.50,70.72]	[29.83,61.78]

Note: The rows correspond to the shocks targeting business-cycle frequencies variation in unemployment (MBC shock) for the various financial VARs described in the text. CS denotes the Credit Spread, Cr the measure of credit.

G.4 Description of VECMs

We now fill in the details of the VECMs reported in rows 3 and 4 of Tables 8 and 20-23. Both of these VECMs are nested in the following form:

$$\Delta X_t = \Gamma_0 \Theta X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \nu_t$$

where Θ is the matrix of co-integration coefficients and Γ_0 is the matrix of loadings of these co-integration relationships. The difference between the two VECMs is the specification of the number of unit roots and the co-integration relations.

In VECM$_1$, we assume that the real quantities (Y, C, I, APL) and TFP share a single stochastic trend, while the remaining variables are assumed to be stationary. The co-integrating relationship is of the type $x_t = \alpha_x + \beta_x TFP_t$ for each variable $x \in \{Y, C, I, APL\}$.

In VECM$_2$, the real quantities (Y, C, I, APL) and TFP share one stochastic trend; the nominal variables, π and R, share another stochastic trend; and the remaining variables (the unemployment, hours, and the labor share) are stationary. The co-integration relationships are of the type $x_t = \alpha_x + \beta_x TFP_t$ for $x \in \{Y, C, I, APL\}$ and $R_t = \delta + \gamma \pi_t$.

We have also considered a third specification that allows the number of stochastic trends and the co-integration relationships to be determined completely a-theoretically, by means of the standard maximum eigenvalue and trace tests proposed by Johansen and Juselius (1990). Relative to the aforementioned two specfciations, this "unrestricted" VECM marginally reinforces the disconnect between the short run and the long run;[48] but it also produces six (!) unit roots, which makes little sense from the perspective of theory.

G.5 Measuring the Relative Price of Investment

We now describe the measure of the relative price of investment that is used in one of our robustness exercises, the one appearing as row 9 ("Extended") of Tables 8 and 20-23.

Let P_t^x denote the chained price index of aggregate x at time t, and similarly Q_t^x the quantity of aggregate x at time t, where x can denote either gross domestic private investment (GPDI), durable consumption (D), non durable consumption (ND) or services (S). The change in investment (I=GPDI+D) price, is then given by

$$\Delta P_t^{\mathrm{I}} = \sqrt{\Delta P_t^{\mathrm{I}}(Q_{t-1}^{\mathrm{I}}) \Delta P_t^{\mathrm{I}}(Q_t^{\mathrm{I}})} - 1$$

[48] In particular, the unemployment shock accounts 10% of the long-run volatility in output and TFP, compared to 14% in VECM$_1$ or $VECM_2$.

where

$$\Delta P_t^{\mathrm{I}}(Q_{t-1}^{\mathrm{I}}) = \frac{P_t^{\mathrm{GPDI}} Q_{t-1}^{\mathrm{GPDI}} + P_t^{\mathrm{D}} Q_{t-1}^{\mathrm{D}}}{P_{t-1}^{\mathrm{GPDI}} Q_{t-1}^{\mathrm{GPDI}} + P_{t-1}^{\mathrm{D}} Q_{t-1}^{\mathrm{D}}} \text{ and } \Delta P_t^{\mathrm{I}}(Q_t^{\mathrm{I}}) = \frac{P_t^{\mathrm{GPDI}} Q_t^{\mathrm{GPDI}} + P_t^{\mathrm{D}} Q_t^{\mathrm{D}}}{P_{t-1}^{\mathrm{GPDI}} Q_t^{\mathrm{GPDI}} + P_{t-1}^{\mathrm{D}} Q_t^{\mathrm{D}}}$$

Similarly, we define the change in the consumption (C=ND+S) price as

$$\Delta P_t^{\mathrm{C}} = \sqrt{\Delta P_t^{\mathrm{C}}(Q_{t-1}^{\mathrm{C}}) \Delta P_t^{\mathrm{C}}(Q_t^{\mathrm{C}})} - 1$$

where

$$\Delta P_t^{\mathrm{C}}(Q_{t-1}^{\mathrm{C}}) = \frac{P_t^{\mathrm{ND}} Q_{t-1}^{\mathrm{ND}} + P_t^{\mathrm{S}} Q_{t-1}^{\mathrm{S}}}{P_{t-1}^{\mathrm{ND}} Q_{t-1}^{\mathrm{ND}} + P_{t-1}^{\mathrm{S}} Q_{t-1}^{\mathrm{S}}} \text{ and } \Delta P_t^{\mathrm{C}}(Q_t^{\mathrm{C}}) = \frac{P_t^{\mathrm{ND}} Q_t^{\mathrm{ND}} + P_t^{\mathrm{S}} Q_t^{\mathrm{S}}}{P_{t-1}^{\mathrm{ND}} Q_t^{\mathrm{ND}} + P_{t-1}^{\mathrm{S}} Q_t^{\mathrm{S}}}$$

Let us denote by Q_t the relative price of investment as $Q_t = P_t^{\mathrm{I}}/P_t^{\mathrm{C}}$, then Q_t satisfied

$$Q_t = (1 + \Delta P_t^{\mathrm{I}} - \Delta P_t^{\mathrm{C}}) Q_{t-1}$$

H Bayesian vs Classical Approach

In this Appendix we first describe the details of the Minnesota prior we used to make Bayesian inference from our VARs. We then explore how the main results are robust to a "classical" alternative.

H.1 Priors

We used the Minnesota prior, which incorporates the prior belief that the endogenous variables included in the VAR follow either a random walk process or a stationary AR(1) process. For a VAR(p) process of the form

$$X_t = C + \sum_{k=1}^{p} A^{(k)} X_{t-k} + u_t$$

where $X_t = (x_{1t}, \ldots, x_{Nt})$, the Minnesota prior implies $C = \mathbf{0}$,

$$A^{(1)} = \begin{pmatrix} a_{11} & 0 & \ldots & 0 \\ 0 & a_{22} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & a_{NN} \end{pmatrix} \quad \text{with} \quad a_{ii} = \begin{cases} 1 & \text{if Random walk} \\ \rho & \text{with } |\rho| < 1 \text{ if AR(1)} \end{cases}$$

and $A^{(k)} = \mathbf{0}$ for all $k = 2, \ldots, p$.

In our benchmark experiment, we left the possibility that all variables exhibit a random walk component. However, as a robustness check, we also investigated the case where hours worked, unemployment, the labor share, the inflation rate and the nominal interest rate are, in line with most standard theoretical models, described by stationary AR(1) processes with a persistence, ρ, lower than 1. We found that this is not playing a role for our main results (see Table 27). The Minnesota prior also assumes that the variance of the prior distribution for the coefficients a_{ij} is given by

$$\begin{cases} \left(\frac{\gamma_1}{k^{\gamma_3}}\right)^2 & \text{if } i = j \\ \left(\frac{\sigma_i \gamma_1 \gamma_2}{\sigma_j k^{\gamma_3}}\right)^2 & \text{if } i \neq j \end{cases}$$

and by $(\sigma_i \gamma_4)^2$ for the constant. σ. denotes the standard deviation of the residuals as estimated by a standard OLS regression and k is the lag. Finally the parameters γ_1, γ_2 and γ_4 control for the tightness of the priors on the own lags, other variables lags and the constant term. The parameter γ_3 controls the degree to which coefficients on lags higher than 1 are likely to be zero. We follow Canova (2007, p.380) and use $\gamma_1 = 0.2$, $\gamma_2 = 0.5$, $\gamma_3 = 2$ and $\gamma_4 = 10^5$ which implies a relatively loose prior on the VAR coefficients and an uninformed prior for the constant terms.. The posterior distribution is then computed relying on a Gibbs sampler (see Canova (2007), p. 361-366), performing 50,000 draws and only keeping the last 1,000 draws. We checked the robustness of our results to longer simulations.

H.2 Robustness: Classical vs Bayesian

We now compare our baseline results to two alternatives. The one remains Bayesian but changes the Minnesota prior in the manner described above. The other uses classical inference.

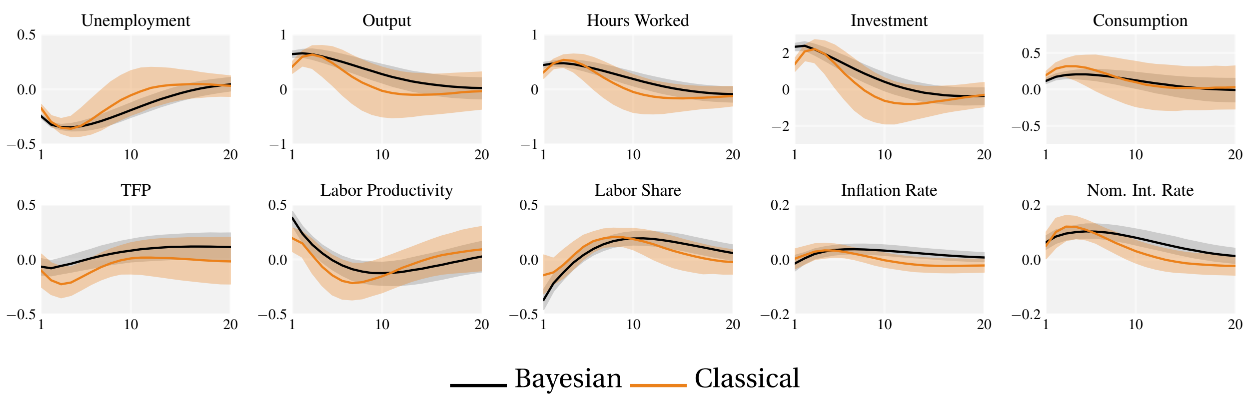
Table 27 and Figure 19 illustrate that the change in the method of inference does not alter the key properties of the MBC shock (defined as the shock that targets unemployment at the 6-32 quarters frequency band). In particular, the change in the prior has a completely negligible effect. And as we move from Bayesian to classical, only two small differences deserve mentioning.

First, the contribution of the MBC shock to the variability of some of the main macroeconomic quantities is somewhat reduced, while it increases for consumption. That is, the MBC shock loses a bit in terms of variance contribution but gains in terms of co-movement.

Second, the MBC shock now accounts for a larger (but still relatively small) share of the variance of TFP over the business cycle frequencies. Note, though, that this finding does not suggest a greater relevance of either RBC or TFP-news types of shocks. As can be seen in Figure 19, the response of TFP to the MBC shock is negative in the short run (while that of output and employment is positive). So the identified MBC shock does not seem to be related to the force that drives business cycles in the RBC model. Moreover, as can be seen in Table 27, the contribution of the MBC shock to long term TFP remains essentially zero, consistent with our baseline results and at odds with TFP-news being the main driver.

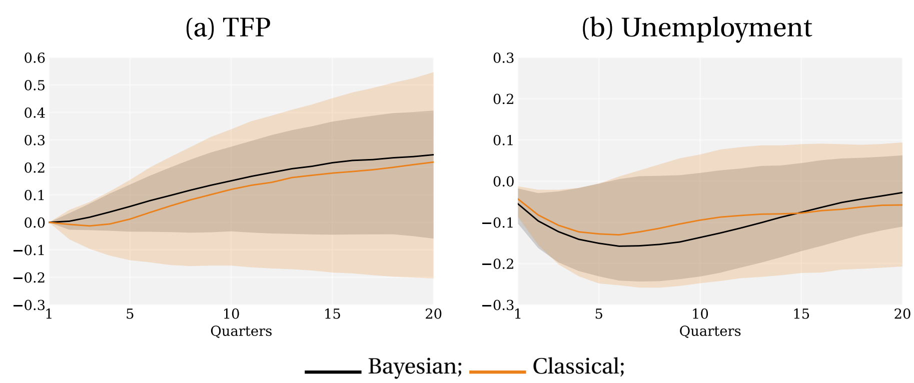
Focusing more explicitly on news shocks, we have also repeated the exercise of Appendix C, which extracts a news shock out of the two factors that drive the majority of TFP at all frequencies, using classical inference. As seen in Figures 21 and 22, the main lesson of that exercise, too, is unaffected: once enough information is used from the data (in the form of sufficiently large VARs), the identified news shock explains a small fraction of the business cycle, despite the fact that it now explains an even larger fraction of the long-run movements in TFP. And as seen in Figure 20, the empirical footprint of the identified news shocks in terms of IRFs is also unaffected.

Figure 19: Impulse Response Functions to the MBC Shock: Bayesian vs Classical Inference



Note: Impulse Response Functions of all the variables in our VAR to the identified MBC shock. Horizontal axis: time horizon in quarters. Gray Shaded area : 68% Highest Posterior Density Interval. Red Shaded area : 68% Confidence Interval obtained from Kilian's (1996) bias corrected Bootstrap.

Figure 20: IRF of TFP and Unemployment to News Shock (Benchmark VAR)



Shaded area: Gray: 68% HPDI Red: 68% Confidence band from 1,000 bootstrap draw

I An AD-AS Example

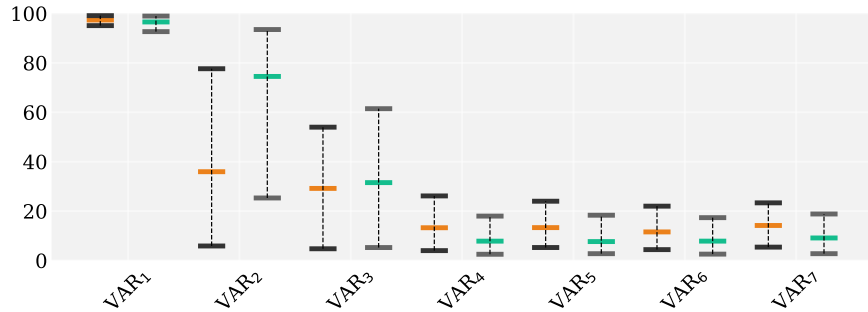
In this appendix we conduct two "pedagogical" exercises motivated by the AD-AS example mentioned in Section 5. In the first, which is semi-structural in nature, we show that the narrative of offsetting

Table 27: Variance Contributions

	u	Y	h	I	C
Short Run (6-32 quarters)					
Bayesian	73.71	58.51	47.72	62.09	20.38
	[66.80,79.94]	[50.65,65.07]	[40.77,54.45]	[54.09,68.46]	[13.61,27.53]
Bayesian (AR)	73.92	58.05	46.95	61.53	19.09
	[67.01,79.67]	[50.33,64.69]	[40.13,53.25]	[53.92,68.09]	[12.92,26.74]
Classical	61.69	50.36	52.23	53.41	36.65
	[54.54,70.54]	[43.45,59.06]	[44.03,60.15]	[45.71,61.08]	[26.09,46.40]
Long Run (80-∞ quarters)					
Bayesian	20.83	4.64	5.45	5.16	4.13
	[8.37,38.94]	[0.52,15.85]	[1.25,15.40]	[0.79,16.81]	[0.38,14.93]
Bayesian (AR)	22.60	5.37	5.08	5.63	5.05
	[10.06,39.49]	[0.58,16.87]	[1.33,16.34]	[0.80,17.25]	[0.53,15.89]
Classical	9.32	5.02	6.33	5.16	4.82
	[2.41,25.35]	[0.55,19.11]	[1.24,19.10]	[0.80,18.73]	[0.52,19.10]
	TFP	Y/h	wh/Y	π	R
Short Run (6-32 quarters)					
Bayesian	5.86	23.91	27.02	6.96	22.27
	[2.44,10.96]	[17.27,31.22]	[18.39,35.93]	[3.24,12.28]	[14.22,30.97]
Bayesian (AR)	5.83	23.41	27.54	6.51	21.87
	[2.71,10.31]	[16.63,30.77]	[19.23,36.24]	[3.17,11.51]	[13.78,29.70]
Classical	19.18	26.51	27.39	14.86	37.50
	[9.18,30.22]	[17.82,35.94]	[17.10,39.71]	[5.92,27.04]	[21.51,55.41]
Long Run (80-∞ quarters)					
Bayesian	4.09	3.88	3.12	5.77	9.12
	[0.41,14.48]	[0.37,14.19]	[0.78,10.16]	[1.70,13.54]	[2.68,20.00]
Bayesian (AR)	5.03	4.95	3.46	5.73	8.36
	[0.54,14.81]	[0.54,14.82]	[0.81,10.85]	[1.64,13.86]	[2.64,19.41]
Classical	5.23	5.22	6.00	7.30	9.50
	[0.72,20.06]	[0.61,19.57]	[1.16,19.97]	[1.88,18.02]	[2.64,21.51]

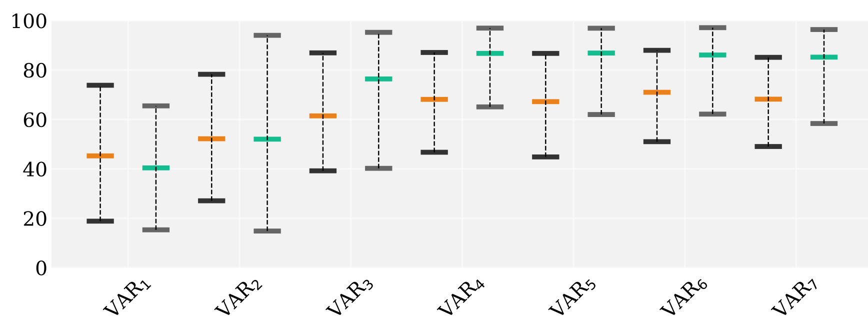
Note: Variance contributions of the MBC shock at two frequency bands. The first row (Short Run) corresponds to the range between 6 and 32 quarters, the second row (Long Run) to the range between 80 quarters and ∞. The shock is constructed by targeting unemployment over the 6-32 range. 68% HPDI into brackets in the Bayesian case. In the Classical exercise, we report the 68% confidence band obtained from Kilian's (1996) bias corrected Bootstrap. The Bayesian (AR) case corresponds to the situation where the priors assume that unemployment, hours worked, inflation, the interest rate, the labor share are stationary AR processes.

Figure 21: Variance Contribution of News Shock to Unemployment



Note: Contribution of news shock to unemployment at business-cycle frequencies. Red (resp. Green) line gives median for the Bayesian (resp. Classical) case, upper and lower black lines give 68% HPDI. $\text{VAR}_1 = \{u,\text{TFP}\}$, $\text{VAR}_2 = \text{VAR}_1 \cup \{I\}$, $\text{VAR}_3 = \text{VAR}_2 \cup \{Y, C, h\}$, VAR_4 = Baseline VAR, $\text{VAR}_5 = \text{VAR}_4 \cup \{SP500\}$, $\text{VAR}_6 = \text{VAR}_5 \cup \{\text{utilization}\}$, $\text{VAR}_7 = \text{VAR}_6 \cup \{\text{credit spread}\}$.

Figure 22: Long-Run Variance Contribution of News Shock to TFP



Note: Contribution of news shock to unemployment at business-cycle frequencies. Red (resp. Green) line gives median for the Bayesian (resp. Classical) case, upper and lower black lines give 68% HPDI. $\text{VAR}_1 = \{u,\text{TFP}\}$, $\text{VAR}_2 = \text{VAR}_1 \cup \{I\}$, $\text{VAR}_3 = \text{VAR}_2 \cup \{Y, C, h\}$, VAR_4 = Baseline VAR, $\text{VAR}_5 = \text{VAR}_4 \cup \{SP500\}$, $\text{VAR}_6 = \text{VAR}_5 \cup \{\text{utilization}\}$, $\text{VAR}_7 = \text{VAR}_6 \cup \{\text{credit spread}\}$.

demand and supply shocks does not work insofar as the supply shock is proxied by the productivity shock identified via our method. In the second exercise, which is fully structural, we show that this story is also inconsistent with a textbook New Keynesian model calibrate to the relevant elements of our anatomy.

I.1 Proxying the AS shock with the TFP shock

Our first, semi-structural exercise is based on the following simple idea. If the MBC shock is a mixture of an inflationary demand shock and a disinflationary supply shock, and if the supply shock reflects movements in productivity, then the documented disconnect between the MBC shock and inflation should be weakened, and the role of the demand shock be revealed, if we control for the effect of productivity. This in turn can be done by purging from the data the reduced-form shock that targets TFP over the business-cycle frequencies.[49] We thus repeat our identification of the shocks that target unemployment, GDP, and inflation after this purging and ask whether this reduces the disconnect between the MBC shock and inflation.

As evident in Table 28 and Figure 23, the answer is clearly negative. Whether we look at original reduced-form shocks or the ones obtained after purging the effects of productivity, the aforementioned disconnect and indeed the shocks themselves remain almost unchanged.

Table 28: Variance Contributions

	u	Y	π
Unemployment Shock			
Baseline	73.71	58.51	6.96
Purged	70.98	61.10	8.05
Output Shock			
Baseline	56.24	80.13	10.47
Purged	57.48	78.29	9.55
Inflation Shock			
Baseline	4.24	7.88	83.03
Purged	3.78	6.04	79.97

68% HPDI into brackets

Furthermore, insofar as one accepts the interpretation of the MBC shock identified in the data as the

[49] We have obtained almost identical results with a variant specification that proxies the supply shock with the technology shock identified as in Galí (1999), as well as with one that purges both the short-run and the long-run TFP shocks identified via our method. These alternatives, however, seem less appropriate for the present purposes, because they amount to purging also the effects of news about future productivity, which in standard models maps do a demand rather than a supply shock.

Figure 23: Impulse Response Functions

(a) Unemployment Shock

(b) Output Shock

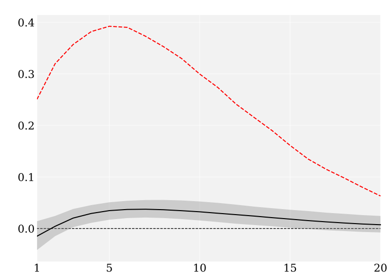
(c) Inflation Shock

——— Baseline Model, - - - - Purged for TFP, Shaded area: 68% HPDI.

AD shock in the theory, the challenge for the theory is twofold: not only does the MBC shock accounts for a small fraction of volatility in inflation, but it has such a small impact on inflation that the theory can make sense of only if the AS curve is extremely flat.

We illustrate this point in Figure 24. The solid black line shows the actual response of inflation to the MBC shock in the data. The dashed red line shows the response predicted by the New Keynesian Philips Curve, under a textbook calibration and with the real marginal cost proxied by the response of the labor share to the MBC shock.[50] The large gap between the two lines illustrates that, even after controlling for the possible sluggishness in the response of the real marginal cost due to wage rigidities, the predicted response of inflation is over 10 times larger than the actual one. Conversely, the Philips curve has to be very flat for the theory to match the observed inflation response. A similar picture is painted in the next subsection, which takes a fully-structural approach to both the MBC shock and the shock that accounts for the volatility in inflation.

Figure 24: The MBC Shock and the NKPC



——— Actual inflation response; Shaded area: 68% HPDI; - - - - Predicted response.

[50]To construct this line, we proceed as follows. First, we take the New Keynesian Philips Curve: $\pi_t = \kappa x_t + \beta \mathbb{E}_t[\pi_{t+1}]$, where $\beta \in (0,1)$ is the discount factor, $\kappa = (1-\theta)(1-\beta\theta)/\theta$, and θ is the Calvo parameter. Next, we set $\theta = 2/3$ (prices are, on average, reset every 3 quarters) and $\beta = 0.99$ (an annual discount rate of 4%). Finally, we feed x_t with the response of the labor share to the MBC shock.

I.2 A 2x2 New Keynesian model

We now turn to second, fully-structural exercise: we employ a two-shock, two-variable version of the New Keynesian model and ask what it takes for this model to account for the relevant elements our anatomy.

In particular, we estimate both the shock processes and the main parameters of the model—those that govern the slopes of the AS and AD curves and the sluggishness of the inflation and output dynamics—by minimizing the distance between four empirical IRFs and their theoretical counterparts. These are the IRFs of output and inflation to the output shock and to the inflation shock, as identified by our method. We focus on these objects because the simple, textbook-style model considered here is meant to speak to the only dynamics of output and inflation.[51]

We then use the estimated model to answer two questions. First, what parameter values (for instance, the slope of the Phillips curve) does the model need in order to achieve maximum fit vis-a-vis our facts? And second, does the MBC shock identified via our method correspond to a single structural shock in the model or to a mixture of structural shocks, as suggested by the AD-AS example used in Section 5?

Like the textbook version of the New Keynesian model, the version considered here reduces to two equations in the (y,π) space, one representing aggregate demand (AD) and the other representing aggregate supply (AS). At the same time, our version mimics richer DSGE versions by allowing for a flat Philips curve, habit persistence and price indexation. These enhancements may lack empirical microfoundations but are customarily used in the literature in order to improve the model's empirical performance.

Let us start with the textbook version of the New Keynesian model, which can be expressed by the following equations:

$$y_t = -\sigma\,(R_t - \mathbb{E}_t[\pi_{t+1}]) + \mathbb{E}_t[y_{t+1}] + \sigma\,\xi_t \tag{3}$$

$$\pi_t = \lambda\, mc_t + \beta\mathbb{E}_t[\pi_{t+1}] + \lambda\,\mu_t \tag{4}$$

$$mc_t = \kappa\, y_t - \tfrac{1+\nu}{\alpha}\, a_t + \varsigma_t \tag{5}$$

$$R_t = \varphi\pi_t + \psi y_t + m_t \tag{6}$$

The interpretation is familiar: (3) is the Dynamic IS curve, (4) is the NKPC, (5) describes the real marginal cost as a function of output and productivity, and (6) specifies monetary policy. The notation is also standard: y_t is output, π_t is inflation, mc_t is the real marginal cost, R_t is the nominal interest rate, $\mathbb{E}_t$ is the rational expectations operator, a_t is the productivity shock, ξ_t is the discount-rate shock, μ_t is

[51] The empirical IRFs are obtained from our VAR by targeting the inflation rate or output (see Figure 2 for example). The theoretical IRFs are constructed in an analogous manner, treating the model as the DGP.

the markup shock, ς_t is the cost-push shock, m_t is the monetary-policy shock, $\sigma > 0$ is the elasticity of intertemporal substitution, $\beta \in (0,1)$ is the steady-state discount factor, $\lambda \equiv \frac{(1-\theta)(1-\beta\theta)}{\theta}$ is the slope of the NKPC with respect to the real marginal cost (and to the markup shock, too), θ is the Calvo parameter (the probability of a firm's not being able to reset its price), $\kappa \equiv \frac{1+\nu}{\alpha} + \frac{1-\sigma}{\sigma} > 0$ is the slope of the real marginal cost with respect to output, $\nu \geq 0$ is the Frisch elasticity of labor supply, $\alpha \in (0,1]$ is the short-run elasticity of output with respect to labor, and $\varphi > 1$ and $\psi \geq 0$ parameterize the responsiveness of monetary policy to, respectively, inflation and output.

To simplify the exposition of the AD and AS curves below, we set $\psi = 0$.[52] For the reported experiments, we also interpret a period as a quarter and set $\beta = .99$, $\varphi = 2$, $\alpha = 1$, and $\nu = 0$.[53] More crucially, the parameters λ and σ, which govern the slopes of the two curves, and two additional parameters, which are introduced momentarily and which govern the endogenous persistence in the model, are left free to be estimated in one of the experiments.

Substituting (6) in (3) and (5) in (4), we can reduce the model to the following two equations in output and inflation alone:

$$y_t = -\sigma\varphi\pi_t + \sigma\mathbb{E}_t[\pi_{t+1}] + \mathbb{E}_t[y_{t+1}] + u_t^d \tag{7}$$

$$\pi_t = \lambda\kappa y_t + \beta\mathbb{E}_t[\pi_{t+1}] - u_t^s \tag{8}$$

where $u_t^d \equiv \sigma\xi_t - \sigma m_t$ and $u_t^s \equiv \lambda\kappa a_t - \lambda\kappa\varsigma_t - \lambda\mu_t$. Condition (7) represents aggregate demand, AD, (8) represents aggregate supply, AS. Accordingly, u_t^d and u_t^s are the (composite) demand and supply shocks. We assume that these shocks follow independent $AR(1)$ process and let (σ_d, σ_s) denote their standard deviations and (ρ_d, ρ_s) their autocorrelations.

This completes the description of the baseline version of the New Keynesian model, which is the building block for the enhanced, DSGE-like variant used here. This variant is obtained by including habit persistence in the Dynamic IS curve and by replacing the standard NKPC with the hybrid one. The modified equations are given by

$$\begin{aligned} y_t &= -\sigma\frac{1-h}{1+h}(\varphi\pi_t - \mathbb{E}_t\pi_{t+1}) + \frac{1}{1+h}\mathbb{E}_t y_{t+1} + \frac{h}{1+h}y_{t-1} + u_t^d \\ \pi_t &= \lambda\left(\kappa y_t + \frac{h}{\sigma(1-h)}\left(y_t - y_{t-1}\right)\right) + \frac{\beta\theta}{\theta+\omega(1-\theta(1-\beta))}\mathbb{E}_t\pi_{t+1} + \frac{\omega}{\theta+\omega(1-\theta(1-\beta))}\pi_{t-1} - u_t^s \end{aligned}$$

[52] Since the experiments conducted here do not utilize data on the interest rate, the effect of a positive ψ on the dynamics of output and inflation can be proxied by appropriately adjusted values for other model parameters. Accordingly, we have verified that our findings about the model's performance remain essentially unchanged if we let, for example, $\psi = 0.5$.

[53] The values of β and φ are standard, while those for α and ν help reduce the sensitivity of the real marginal cost to output (intuitively, a high value for α mimics variable utilization and a low value for ν mimics real wage rigidity), which in turn helps improve the empirical performance of the model (and makes our own job harder)

for some $h \in [0,1)$ and $\omega \in [0,1)$. These capture the inertia added to the aggregate demand and aggregate supply equations, respectively.[54] Finally, λ is allowed to take low enough values so as to accommodate a relatively weak positive co-movement between inflation and output in response to demand shocks.

Let $\Theta \equiv (\sigma_d, \sigma_s, \rho_d, \rho_s; \lambda, \sigma, h, \omega)$ collect the parameters that regulate the shock processes and the internal propagation, namely the slopes of the AS and AD curves and the corresponding sources of sluggishness. We estimate Θ by minimizing the distance between the IRFs of output and inflation to the output and inflation shocks identified in the data via our method and the corresponding objects in the model.

Table 29 reports the estimated parameter values. Table 30 reports the variance contributions of the model's two structural shocks. The most notable features are that λ is nearly zero, that the output fluctuations are dominated by a non-inflationary demand shock, and that the inflation fluctuations are dominated by a disinflationary supply shock. That is, confronted with the relevant elements of our anatomy, the model demands a very flat AS (or Philips) curve and specialized structural shocks, a picture consistent with that painted in Section 3.[55]

Table 29: Parameters

σ_s	σ_d	ρ_s	ρ_d	h	ω	λ	σ
0.0789	0.0316	0.7016	0.9540	0.1979	0.0000	0.0004	0.2764

Table 30: Variance Contributions

	Output	Inflation
Supply Shock	7.62	98.90
Demand Shock	92.38	1.10

The purpose of this—pedagogical—exercise was to illustrate how the combination of our anatomy with a model can help discipline the AD-AS narrative offered in Section. The same strategy is applied to,

[54]The standard interpretation of h is as the degree of habit persistence in consumption. But as there is no capital in the model, h represents all the adjustment frictions in aggregate demand. One the other hand, ω corresponds to the fraction of irrational, backward-looking firms in Galí and Gertler (1999), or the degree of automatic past-price indexation in Christiano, Eichenbaum, and Evans (2005). These model enhancements lack solid empirical micro-foundations but are customarily used in the DSGE literature.

[55]Another interesting finding, which is though not particular relevant for the present purposes, is that the estimation of the model based on our anatomy yields $\omega = 0$, that is, no past-price indexation or backward-looking element in the Philips curve. This appears to be driven by the absence of sluggishness in the response of inflation to the inflation shock and suggests that the "right" model is one that somehow allows for such sluggishness in the response of inflation to the main driver of the real quantities without however introducing such sluggishness in the overall inflation dynamics.

and works well for, the three state-of-the-art DSGE models considered in Section 6. Naturally, while all of these exercises support the interpretation of the empirical MBC shock as a non-inflationary demand shock, they cannot establish its universality.

J Robustness of Model Evaluations

This appendix assesses the robustness of the lessons drawn in Section 6 regarding the evaluation of the JPT and ACD models under the lenses of our method.

J.1 Running the Same VAR on Data and Models

In the main text, we evaluated the ability of JPT and ACD to account for the MBC shock in the data using the theoretical, asymptotic properties of the two models. We now explore the robustness of our findings to a Monte Carlo exercise that runs the same, small-size VAR on artificial data from each model and on the actual US data.

Because both models have a stochastic dimension smaller than that of our benchmark VAR, first rerun our empirical specification on a restricted VAR featuring Output, Consumption, Investment, Hours worked, Fernald's measure of Total Factor Productivity (corrected for utilization), the nominal interest rate and the inflation rate. As can be seen in the first row of Figure 25, this smaller VAR gives rise to the same picture as our baseline VAR: the shocks that target output, hours, investment and consumption are essentially indistinguishable from one another.

Because the smaller VAR run here has exactly the same stochastic dimension as the JPT model, it can be readily run on artificial data generated by that model. By contrast, the ACD model has one dimension less: being a flexible-price, no-monetary model, it is makes no prediction about inflation (and nominal variables). To be able run the same VAR on artificial date from that model, we augment it with the simplest model of inflation we could think of: an exogenous AR(1) process.[56] Clearly, this add-on has no effect on the model's predictions regarding any of the real variables. It only permits us to run the same VAR on the two models under consideration.

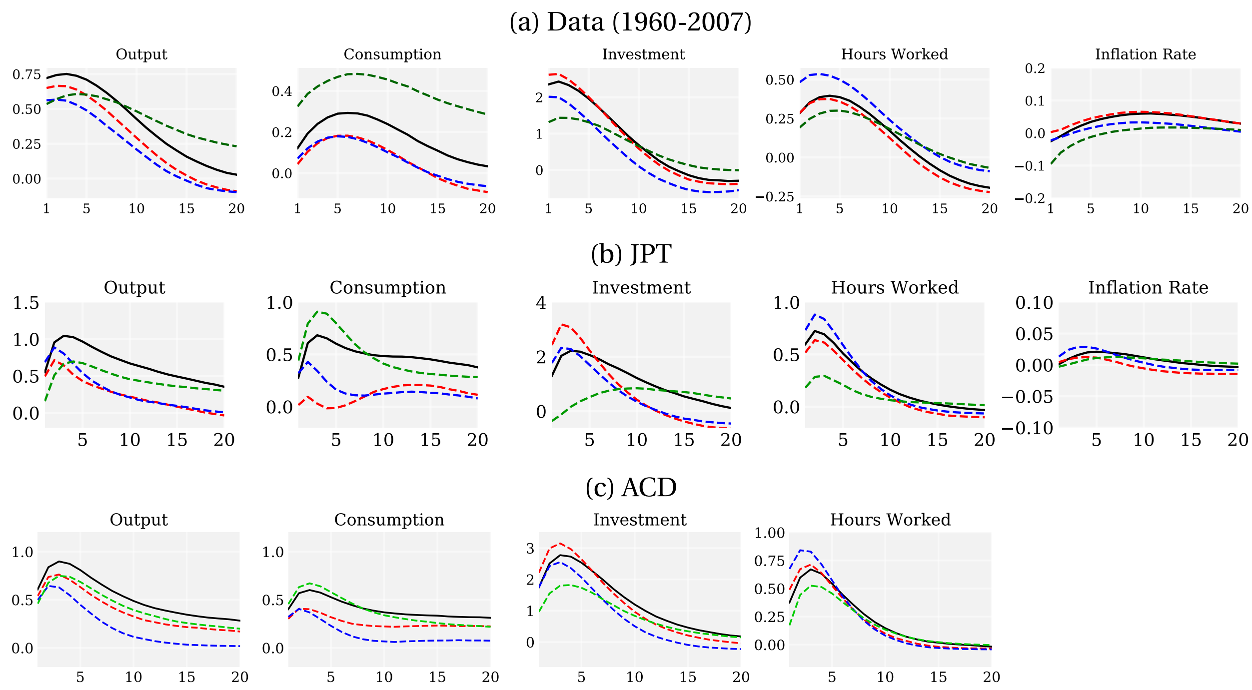
Each model is then simulated 1000 times to generate artificial time series for the aforementioned set of variables. Each artificial time series has the same length as in the data (192 quarters from 1960Q1 to

[56] We estimated this process using inflation data alone. This gave an estimate of 0.89 for the persistence parameter and 0.27% for the standard deviation of the innovation. All the other (real) parameters of the model were fixed at their values in the original article. Finally, the nominal interest rate was obtained directly from the Fisher equation, using the AR(1) process for inflation and the model's prediction about the real rate.

2007Q4). Note that, in order to avoid any dependence on initial conditions, we actually simulated 292 observations and discarded the first 100. Then, for each set of simulated data, we estimated the same VAR as in actual data and applied our methodology to extract the various VAR-based shocks, or "factors," and build their IRFs.

The second and the third row of Figure 25 show the median of the so-obtained distribution of IRFs for the JPT and ACD models, respectively. The comparison of these rows to one another and with the first row (the data) corroborates the lesson obtained in the main text on the basis of the theoretical state-space representation of the two models: the factors in JPT are less interchangeable than their counterparts either in ACD or the data. The visual impression is corroborated by Table 31, which reports the metric discussed in the main text.

Figure 25: The MBC Shock



Y shock; I shock; h shock; C shock; Shaded area: 68% HPDI.

J.2 Re-estimating JPT/ACD

We now turn to the remaining two robustness exercises mentioned in Section 6.

First, in order to offer a proper comparison between JPT and ACD, we re-estimated the JPT model the same frequency-domain Bayesian technique used to estimate ACD. More precisely, the model is estimated over the business-cycle band of frequencies (6-32 quarters), using the levels of all variables, and

Table 31: Interchangeability of Factors, Simulated VARs

	Y	C	I	h	Average
Data	0.47	0.52	1.28	0.28	0.64
JPT	0.80	0.90	2.58	0.42	1.17
ACD	0.42	0.47	1.34	0.25	0.62

Note: The metric is the same as that in Table 9. A number closer to zero indicates a larger degree of interchangeability.

using the 1960-2007 data. This set of results is labeled *JPT - Freq. Domain* in the tables and figures that follow.

Second, we re-estimated both models using a minimum-distance estimation technique, with the parameters selected in order to minimize the distance between IRFs of output, consumption, investment and hours worked to the output, consumption, investment and hours worked factors over the horizon of 20 quarters (a set of 320 moments). Denoting by $IRF^i_{j,h}$ (resp. $\widetilde{IRF}^i_{j,h}(\Theta)$) the response of variable j to factor i at horizon h found in the data (resp. in the model) and $\sigma^i_{j,h}$ the variance of $IRF^i_{j,h}$, the vector of structural parameters Θ is found by solving the problem

$$\min_{\Theta} \sum_{i=1}^{4} \sum_{j=1}^{4} \sum_{h=1}^{20} \frac{(\widetilde{IRF}^i_{j,h}(\Theta) - IRF^i_{j,h})^2}{\sigma^i_{j,h}}$$

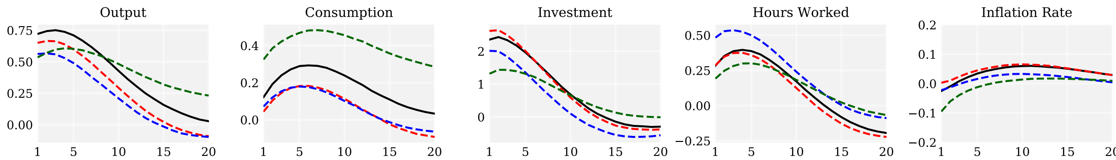
Given our focus on the real IRFs, the parameters pertaining to the nominal part of JPT (Calvo probabilities, indexation parameters, parameters of nominal shocks) are not identified. We therefore set the values of these parameters to those estimated by JPT and re-estimated the parameters pertaining to the real side of the model (preferences, technology, adjustment costs, parameters of real shock processes). The relevant set of results is labeled *JPT - Matching Factors* and *ACD - Matching Factors*.

Figure 26 and Table 32, which extend Figure 6 and Table 9 from the main text, provide a comprehensive comparison of the dynamic properties of the two models under alternative specifications. The main findings are as follows. Re-estimating the JPT model in the frequency domain has a significant but still insufficient impact on the model's ability to reproduce the interchangeability of factors in the data. Re-estimating it by targeting the factors helps the model even more, but it still falls short of that in the data. Re-estimating the ACD by targeting the factors does not upset its already good performance, but it overshoots in the direction of producing too much interchangeability. All in all, the metric of how different the factors are is systematically greater for JPT than ACD, irrespective of the estimation method.

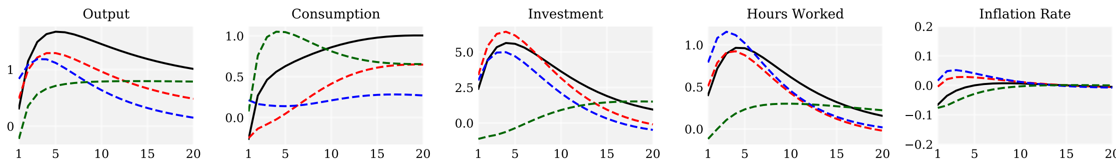
In conclusion, let us reiterate that the main goal of the application of our method to ACD and JPT

Figure 26: Comparing Business-Cycle Factors

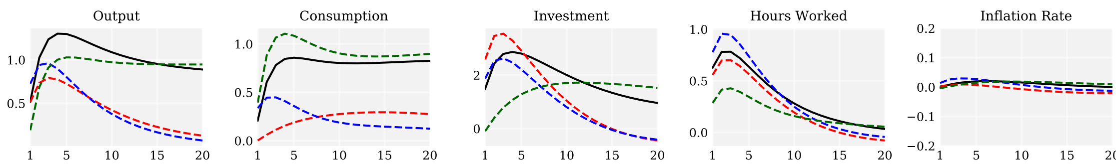
(a) Data (1960-2007)



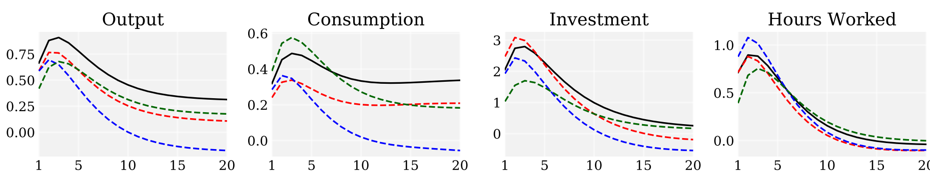
(b) JPT - Original



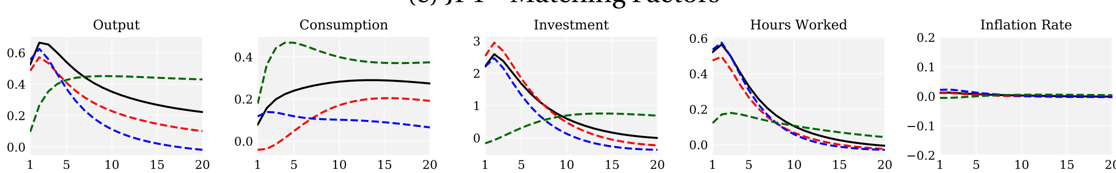
(c) JPT - Frequency Domain



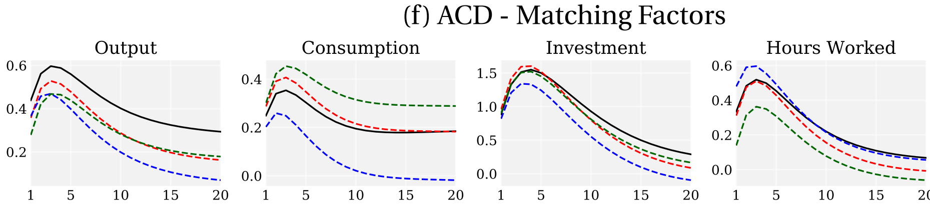
(d) ACD



(e) JPT - Matching Factors



(f) ACD - Matching Factors



Output; Investment; Hours Worked; Consumption.

Table 32: Interchangeability of Factors

	Y	C	I	h	Average
Data (1960-2007)	0.47	0.52	1.28	0.28	0.64
JPT - Original	2.90	2.21	6.29	1.35	3.19
JPT - Freq. Domain	1.41	1.42	3.24	0.42	1.62
ACD	0.56	0.49	1.61	0.30	0.74
JPT - Matching Factors	0.56	0.51	2.26	0.27	0.90
ACD - Matching Factors	0.26	0.36	0.49	0.26	0.34

Note: The metric is the same as that in Table 9. A smaller number indicates greater interchangeability.

is not to judge the superiority of one model over the other, but rather to illustrate the probing power of our method in the context of existing, medium-scale, DSGE models that have already been estimated and evaluated via other methods. This is best exemplified by the exercise conducted in the main text. The second robustness exercise in this appendix serves a complementary objective, namely to inform on whether is at all possible for these models to be replicate the propagation mechanism we observe in the data and, if so, what this requires in terms of their parameters. In short, the two exercises illustrate two different ways in which our anatomy of the data can inform theory.

K The Secondary Business Cycle Shock

For each of the five macroeconomic quantities, $X \in \{u, Y, h, I, C\}$, we now identify *two* shocks. The first shock is the one already reported in the main text: it is obtained by maximizing its contribution to the business-cycle volatility of that variable. The second shock is obtained by maximizing its contribution to the residual, business-cycle volatility of the targeted variable after filtering out the effect of the first shock. This procedure produces a collection of five new shocks, one for each of the macroeconomic quantities of interest.

Figure 27 reports the IRFs to these shocks and Table 33 their variance contributions. The IRFs are nearly the same, suggesting that these shocks, too, represent interchangeable facets of one shock—the "secondary" business cycle shock, or SBC for short.

Figure 27 also reveals that the impact of the SBC shock on the economy builds up slowly over time, peaking after several quarters. By contrast, the impact of the MBC shock peaks within a year and fades shortly after. Furthermore, the SBC shock contains relatively more information about TFP and the prospects of the economy in the medium to long run. In this sense, whereas the MBC shock fits the profile of a

Figure 27: The Various Facets of the SBC Shock, IRFs

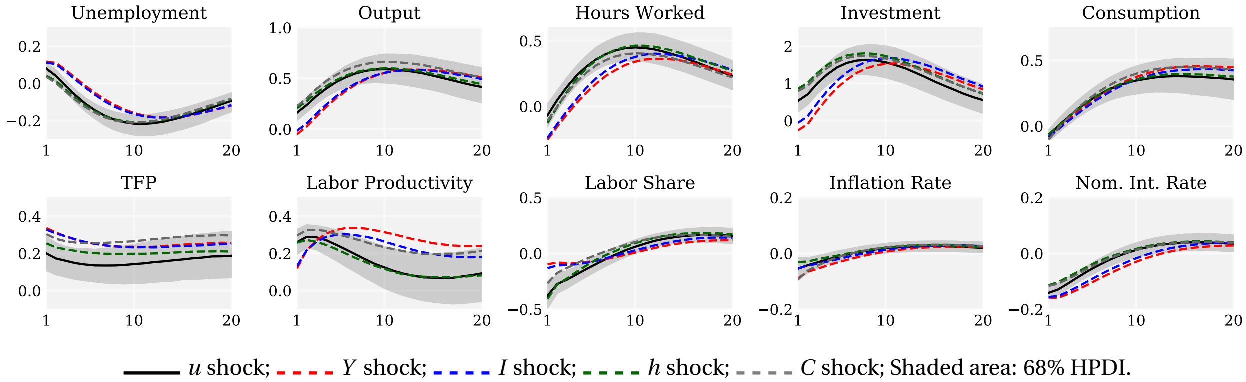


Table 33: Variance Contributions of Second Largest Shocks

Target	u	Y	h	I	C
Unemployment	24.50	21.49	23.76	19.73	21.41
	[18.61,31.29]	[15.33,28.89]	[17.41,30.40]	[13.66,27.51]	[15.01,29.22]
Output	23.94	18.54	24.36	17.63	23.08
	[17.80,30.83]	[12.56,25.71]	[17.10,32.15]	[11.55,24.49]	[15.98,31.39]
Hours Worked	21.11	22.59	28.07	24.56	21.92
	[14.99,28.76]	[15.45,30.75]	[21.65,34.19]	[17.12,33.76]	[15.33,29.96]
Investment	24.00	17.99	26.08	18.41	22.23
	[17.82,30.91]	[11.98,25.21]	[18.77,33.67]	[12.18,25.47]	[15.44,30.75]
Consumption	20.90	26.19	22.23	22.90	28.00
	[14.06,28.17]	[18.58,35.60]	[15.77,29.44]	[14.63,31.78]	[21.31,34.84]
	TFP	Y/h	Wh/Y	π	R
Unemployment	5.71	19.84	26.44	11.08	38.49
	[2.16,11.87]	[14.26,26.43]	[17.47,36.69]	[4.38,20.46]	[28.16,48.05]
Output	17.79	17.16	6.46	20.55	53.85
	[9.10,29.06]	[11.33,24.25]	[2.16,13.23]	[10.19,33.00]	[43.53,62.99]
Hours Worked	10.15	17.60	29.44	8.10	28.54
	[4.72,18.29]	[11.30,24.42]	[19.92,39.71]	[3.27,16.17]	[18.83,39.20]
Investment	17.52	16.37	8.59	12.14	51.56
	[8.56,28.84]	[10.67,23.05]	[3.25,16.75]	[4.31,23.20]	[40.34,61.00]
Consumption	13.48	21.38	15.68	21.52	30.63
	[6.43,22.85]	[15.09,28.84]	[7.04,25.63]	[12.81,31.48]	[19.76,41.06]

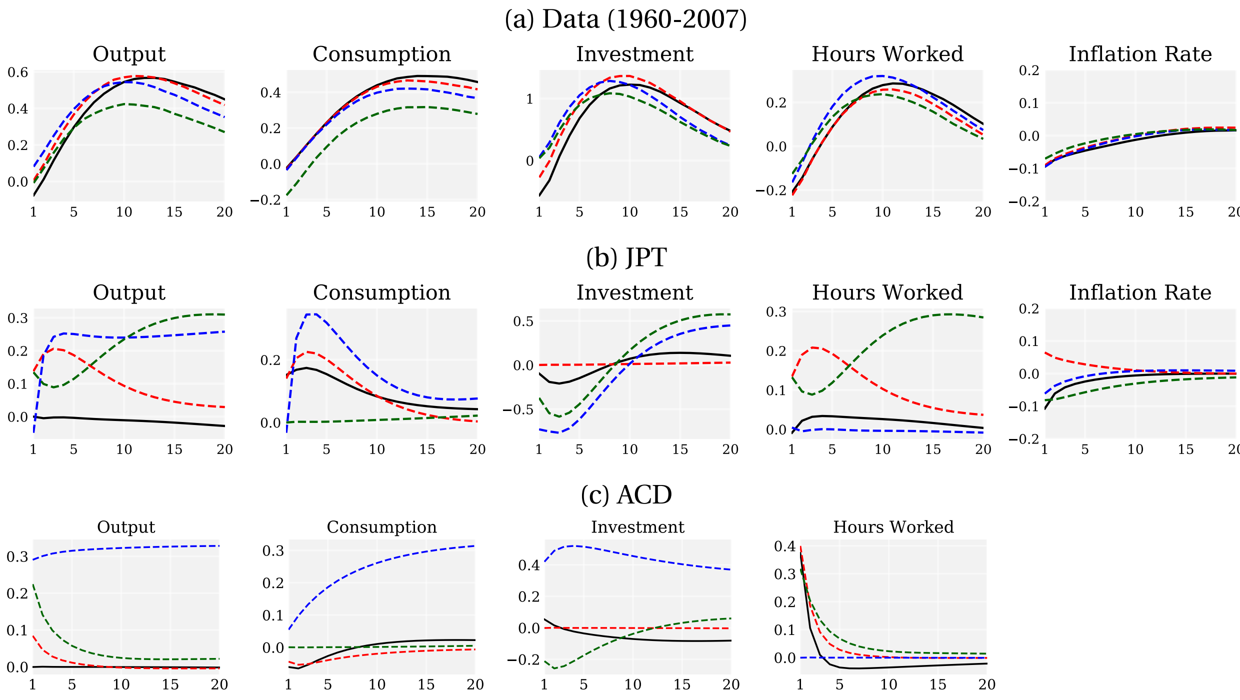
quick-moving demand shock, the SBC shock fits the profile of a slow-moving supply shock. Both shocks, however, have a similar, zero to weakly positive, effect on inflation. Neither of them therefore fits easily in the traditional AD-AS framework.[57]

In the main text, we focused on the MBC shock as the main probing tool of our anatomy and treated the SBC shock as part of the residual. While the SBC shock represents subsidiary rather than primary variation in the data, it can still serve as an additional or complementary validation tool in exercises like those conducted in Section 6. For instance, consider Figure 28. This figure redoes Figure 6 for the SBC shock in place of the MBC shock. That is, it compares the various second largest shocks to the corresponding objects in JPT and ACD, the models considered in Section 6. Clearly, JPT does rather poorly vis-a-vis the SBC shock, too. But now this failure is shared by ACD.

On the one hand, these findings confirm the validation prowess of our empirical strategy. On the other hand, they serve as an additional warning that the postulated propagation mechanisms of state-of-the-art models, even of the most successful ones, remain crude representations of the propagation mechanisms that best characterize the data.

[57] Of course, any attempt to offer a structural interpretation of the MBC and SBC shocks, either jointly or in isolation, faces the basic challenge discussed in detail in Section 5 that such objects could be different combinations of multiple theoretical shocks, none of which fits the profile of either of these empirical objects. The aforementioned interpretation is therefore possible but not necessary.

Figure 28: The SBC in the Data and the Models



Output; Investment; Hours Worked; Consumption.