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BUSINESS CYCLE ANATOMY

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This paper subsumes our prior empirical work on this subject, different incarnations of which appeared in Section 2 of Angeletos, Collard, and Dellas (2015), the 2013 Schumpeter Lecture at the NASM of the Econometric Society, the 2013 Hydra Workshop in Taormina, the 2015 Bank of Portugal Conference, and the 2016 Meeting of the European Economic Association. We thank Patrick Feve, Lars Hansen, Franck Portier, Juan Rubio-Ramirez and various seminar participants for useful comments. Angeletos acknowledges the financial support of the National Science Foundation (Award #1757198). We finally have no financial conflicts or interests to disclose. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

We dissect the comovement patterns of the macroeconomic data, identify a single shock that accounts for the bulk of the business-cycle volatility in the key quantities, and use its empirical properties to appraise parsimonious models of the business cycle. Through this lens, the data appears to be at odds with theories that attribute a major role to fluctuations in TFP, to news about future productivity or the long run, and to demand shocks of the New Keynesian type. Instead, it appears to favor theories that allow for demand-driven fluctuations without nominal rigidities and Philips curves. Our findings can also be of use in the evaluation of larger models that employ a multitude of shocks. In this context, we argue that leading DSGE models seem to lack the propagation mechanism observed in the data.

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"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, theoretically inclined economists have often favored models in which a single, recurrent shock acts as the sole, or main, driver of the business cycle.[1] One may be skeptical of such an approach as different business-cycle episodes seem to have had different proximate causes (e.g., an oil shock vs a financial shock). Nonetheless, a parsimonious, single-shock representation may well encapsulate diverse business-cycle triggers if they all operate through a common, dominant propagation mechanism.

This paper aims at shedding new light on what this propagation mechanism looks like. But rather than postulating a particular model and using it to offer a structural interpretation of the data, we do it the other way around. We start with the data, identify a one-shock representation that can successfully capture the bulk of the business cycle, and use its properties (IRFs, variance contributions, etc) to inform theory.[2]

The exercise offers a succinct description of main dynamic comovement patterns in the data. We argue that these patterns are at odds with models that emphasize exogenous or endogenous TFP movements, news about the medium and long run, or demand shocks of the New Keynesian type as important drivers of the business cycle. Instead, the bulk of the business cycle can be attributed to a mechanism that fits the notion of a non-inflationary demand shock.

This finding echoes Beaudry and Portier (2014) and offers support to recent attempts to disentangle demand-driven fluctuations from nominal rigidities and Philips curves, such as Angeletos and La'O (2013), Bai, Ríos-Rull, and Storesletten (2017), Beaudry and Portier (2018), Beaudry, Galizia, and Portier (2018), Benhabib, Wang, and Wen (2015), Huo and Takayama (2015), and Ilut and Saijo (2018). More generally, our approach provides a set of impulse response functions (IRFs) that a successful business-cycle model needs to replicate. It can thus been seen as a complement to Chari, Kehoe, and McGrattan (2007), which also aims at informing the construction of such models but does it in a completely different way, namely, by characterizing the data in terms of deviations from the predictions of the textbook RBC model.

[1] For example, this driver is a monetary shock in Lucas (1973, 1975), a technology shock in Kydland and Prescott (1982), and a sunspot in Benhabib and Farmer (1994).

[2] As is standard in the empirical literature on shocks—see Ramey (2016) for a review—what we are after is not the shock per se but rather its empirical footprint, which embeds the propagation mechanism. 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."

The empirical method. Our method of extracting information from the data builds on Uhlig (2003). We first estimate a VAR on the following key macroeconomic variables: unemployment, GDP, consumption, investment, total hours worked, labor productivity, utilization-adjusted TFP, the labor share, inflation, and the federal funds rate. We next identify the shock that has the maximal contribution to the volatility of unemployment at the business-cycle frequencies (6-32 quarters). We finally compare this shock to other shocks, each one of which is identified by targeting different variables and/or different frequencies. This provides us with a collection of a one-dimensional cuts of the data, or an "anatomy," whose main features and implications for theory are described below.[3]

The main business-cycle shock. Consider the business-cycle frequencies and the following set of variables: unemployment, total hours worked, GDP, and investment. The shock that is identified by targeting any one of these variables is nearly indistinguishable, in terms of IRFs and contribution to variances, from the shock that targets any other variable in that set. Furthermore, any of these shocks triggers positive comovement in all the variables and accounts for about two-thirds of the business-cycle volatility of the targeted variable and for more than one half of the business-cycle volatility in the remaining variables.[4]

This finding motivates the concept of the *main business-cycle shock*: we use this term to refer to the common dynamic patterns encapsulated in any of the identified shocks described above. These patterns in turn form the basis of the lessons we draw for theory. In the context of parsimonious models, the documented IRFs help paint a picture of the "right" model. And in the context of medium-scale models, the invariability of these patterns across targeted variables helps reveal an important weakness of the state of the art.

Disconnect between the short and the long run. The shock that explains the bulk of the business cycle accounts for little of the long-term variation in output, investment, consumption, and labor productivity. Symmetrically, the shock that explains the bulk of the long-term volatility in any of these variables makes a negligible contribution to the business cycle.

This finding complements Blanchard and Quah (1989) and Galí (1999), who argue that the shock that drives productivity and output in the long run accounts for a small fraction, and possibly the wrong sign, of the business-cycle movements in unemployment or hours. It also

[3]While the method used here is a variant of that developed in Uhlig (2003), our application is novel, and so are the facts reported below and the lessons drawn for theory. That paper sought to identify two shocks that jointly drive real GNP in the short to medium run, but faced the challenge of separating one shock from the other. Our application contains two innovations. On the one hand, we bypass the aforementioned challenge by focusing on one-shock cuts of the data. On the other hand, we extract more information from the data by taking multiple such cuts across variables and frequencies. As argued below, the compilation of stylized facts obtained in this way proves exceedingly useful in the context of small and large models alike. Beaudry, Nam, and Wang (2011) and Barsky and Sims (2012) also use variants of Uhlig's method, although for different purposes.

[4]As discussed later on, the consumption response is also positive albeit less tightly connected.

challenges models that, following Beaudry and Portier (2006), emphasize news of the productivity in the long run: in such models, the business cycle is itself a powerful signal of the long run, which is hard to square with our evidence. An alternative, consistent with our evidence, is that the business cycle is driven by belief shifts that are unrelated to productivity and represent news of the *short-term* economic outlook.[5]

Disconnect from TFP at all frequencies. Our main business-cycle shock is disconnected from the variation in TFP at *any* frequency. This is inconsistent with the baseline RBC model, where the business cycle is driven by exogenous technology shocks,[6] as well as with variants of that model that let other shocks, including financial and uncertainty shocks, trigger endogenous fluctuations in aggregate TFP. It is also at odds with versions of the New Keynesian model that tie the shifts in aggregate demand to rational expectations of future TFP (e.g., Lorenzoni, 2009). We next present evidence that represents a broader challenge to that model.

Disconnect from inflation and Phillips curves. In the New Keynesian model, demand shocks induce deviations from flexible-price allocations, which in turn drive inflation.[7] It follows that our main business-cycle shock is consistent with the New Keynesian model only if the cycles it induces are characterized by a strong comovement between the real quantities and inflation.

We instead find that the main business-cycle shock is nearly orthogonal to inflation at *all* frequencies. For instance, the shock that targets unemployment accounts for almost 70% of the business-cycle variation in that variable and only for 10% of the business-cycle variation in inflation. And conversely, the shock that targets inflation explains 80% of the business-cycle variation in inflation and only 9% of the business-cycle variation in unemployment.

A similar disconnect is present between inflation and the labor share, an often-used proxy of the real marginal cost in the New Keynesian literature. Furthermore, the disconnect does not appear to be explained by the offsetting contribution of demand and supply shocks: it survives a purge of the effect of supply shocks, as proxied by the movements in TFP or labor productivity. Finally, the magnitude of the inflation response to the main business-cycle shock is close to zero.

It is possible to bypass these challenges by assuming a sufficiently flat Philips curve and by attributing the residual between actual and predicted inflation to mysterious markup shocks. But it is unclear what these shocks stand for and also whether the required degree of flatness of

[5]See our work in Angeletos, Collard, and Dellas (2017) for a model along these lines and Levchenko and Pandalai-Nayar (2015) for complementary time-series evidence. Broadly consistent is also Bachmann and Zorn (2018), which uses firm-level survey data to argue that the bulk of the short-run variation in investment is accounted by the variation in expectations of demand.

[6]This applies not only to neutral but also to investment-specific technology shocks: the aforementioned disconnect extends to relation between our main business-cycle shock and the relative price of investment.

[7]In the basic New Keynesian model inflation encapsulates the present discounted value of these deviations, just as in the basic asset-pricing model prices encapsulate the present discounted value of dividends.

the Philips curve is consistent with micro-economic evidence.[8] Another possibility, which we find more appealing, is that our main business-cycle shock captures a type of demand-driven fluctuations that, unlike those formalized in the New Keynesian model, do *not* necessarily represent either departures from flexible prices or movements along a Phillips curve.

Medium-scale models. By construction, our empirical strategy is best suited for guiding the construction and evaluation of small models that aspire to capture the business cycle with a single-shock mechanism. Yet, its prodding power extends to larger, DSGE models that employ multiple shocks. We demonstrate this point by deploying our method in two such models.

The first 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). The second is the flexible-price model found in Angeletos, Collard, and Dellas (2017); this is essentially the RBC model augmented with a mechanism that allows waves of optimism and pessimism about the short-run economic outlook to obtain without commensurate movements in either actual or expected TFP. We view the first model as representative of the New Keynesian paradigm and the second as an example of the aforementioned literature that aims at disentangling demand-driven fluctuations from 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 model's shocks, each one constructed by maximizing the business-cycle volatility of a different macroeconomic quantity. In the first model, the theoretical objects turn out to be less interchangeable than their empirical counterparts: they display relatively distinct IRFs and contribute excessively to the variable targeted in their construction. This is because this model—like many other models in the literature—attributes the business cycle to a fortuitous combination of specialized shocks, none of which generates the empirically relevant comovement patterns in the key macroeconomic quantities. By contrast, the model in our prior work replicates the pattern seen in the data because its core mechanism—the variation in expectations of the short run—alone matches the main business-cycle shock in the data.

The objective of these comparisons is not to assert the superiority of the specific model developed in our prior work. Rather, it is to illustrate two broader points: (i) even state-of-the-art DSGE models appear to lack the kind of propagation mechanism encapsulated in our empirical findings; and (ii) the recent literature that aims at disentangling demand-driven business cycles from nominal rigidities and Philips curves holds the promise for rectifying this problem.

Layout. The rest of the paper is organized as follows. Section 2 describes the empirical method. Section 3 reviews our empirical findings and their implications for theory. Section 4

[8]This is the subject of a large literature on menu-cost models and product-level price data (e.g., Golosov and Lucas Jr, 2007; Midrigan, 2011; Bils, Klenow, and Malin, 2012; Alvarez and Lippi, 2014).

contains the application to medium-scale models. Section 5 concludes. The Appendices contain a detailed description of the data, a few additional results, and a number of robustness checks.

2 Data and Method

Our data consists of quarterly observations on the following nine, key macroeconomic variables: GDP, investment, consumption, hours and labor productivity in the non-farm business sector, unemployment, the labor share, inflation (GDP deflator), and the federal funds rate. Appendix A.1 contains precise definitions and data sources. Appendix A.5 establishes the robustness of our results to the inclusion of additional variables, such as stock prices and the relative price of investment. Here, we comment on two choices: the measures of investment and consumptions; and the sample period.

The measure of investment used in our baseline VAR includes consumer expenditure on durables together with gross domestic private investment and changes in inventories, while our measure of consumption consists of consumption expenditure on non-durables and services. In choosing these measures, we follow the standard practice used in the evaluation of models that abstract from durables, such as those considered in Section 4. Appendix A.2 shows the robustness of our results to a VAR that separates business investment from consumption durables.

The sample considered in our baseline VAR starts in the first quarter of 1960 and ends in the last quarter of 2007. The choice of the ending point was based on two considerations. First, it makes our empirical analysis fully compatible with the models studied in Section 4, as these models were originally estimated over 1960-2007. And second, the post-2007 period has been characterized by the zero lower bound and severe financial frictions, features that pose challenges to linear VARs and also are missing from the aforementioned models. Appendix A.3 shows that our results are robust to extending the sample to 2015Q4.

We now turn to the description of the empirical method. This is based on running a VAR on a few key macroeconomic variables and identifying the linear combination of the VAR residuals that contributes the maximum to the forecast error volatility of a particular variable in a particular frequency band (in the time domain). Below, we provide the formal details of this procedure, which, as we have already mentioned, is related to that pioneered by Uhlig (2003) and subsequently used in Barsky and Sims (2012) and Beaudry, Nam, and Wang (2011).

The VAR takes the form

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

where X_t is a $N \times 1$ vector of 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 $A(0) = A_0 = I$, and u_t is the vector of VAR residuals, with $E(u_t u_t') = \Sigma$ for some positive definite matrix Σ.[9]

The Wold representation of the VAR can be written as

$$X_t = B(L)u_t$$

where $B(L) = A(L)^{-1}$ is an infinite matrix polynomial of the form $B(L) = \sum_{\tau=0}^{\infty} B_\tau L^\tau$. We assume that there exists a linear mapping between the VAR innovations, u_t, and some underlying shocks, ε_t, that are mutually independent and normalized to be of unit variance:

$$u_t = S\varepsilon_t$$

where S is a $N \times N$ matrix and ε_t is such that $\mathbb{E}(\varepsilon_t \varepsilon_t') = I$. The shocks in ε_t need not correspond to particular theoretical shocks in a model; they are merely transformations of the VAR residuals. Notwithstanding this qualification, column j of matrix S gives the impact effect of the j-th component of ε on all the variables.

The matrix S has to satisfy $SS' = \Sigma$ but is not uniquely pinned down unless additional restrictions are imposed. In any event, this matrix can be rewritten as $S = \widetilde{S}Q$, where $\widetilde{S}$ is an arbitrary orthogonalization matrix and Q is an orthonormal matrix ($QQ' = I$). In what follows, $\widetilde{S}$ is given by the Cholesky decomposition of the covariance matrix of residuals, so that the ε_t's are obtained by a recursive orthogonalization à la Sims (1980).

For any given orthonormal matrix Q, the VMA(∞) representation of the VAR can be written as follows:

$$X_t = C(L)Q\varepsilon_t = \sum_{\tau=0}^{\infty} C_\tau Q \varepsilon_{t-\tau},$$

where $C_\tau = B_\tau \widetilde{S}$. Column j of matrix C_τ, $C_{\tau,j}$ then gives the impact effect of the j–th element of ε on the VAR variables at horizon τ. By the same token, if we take any column vector q and consider the shock defined by the linear combination $q'\varepsilon_t$, the impact effects of this shock on the same variables at horizon τ, for $\tau \in \{0, 1, ...\}$, is given by

$$\Gamma_\tau = \sum_{j=1}^{N} q_j C_{\tau,j} = C_\tau q.$$

Any structural VAR involves the identification of one or more such column vectors; the sequence $\{\Gamma_\tau\}_{\tau=0}^{\infty}$ then represents the IRFs of the identified shock. For our purposes, the vector q is chosen so as to maximize the contribution of the linear combination $q'\varepsilon_t$ to the volatility of a particular variable k over a particular frequency band $[\underline{\omega}, \overline{\omega}]$. (When studying business-cycle frequencies, we set $\underline{\omega} = 2\pi/32$ and $\overline{\omega} = 2\pi/6$; but we also consider other frequency bands in order to investigate the interaction between the short and the long term.)

[9] The reported results assume two lags, as suggested by the standard Bayesian criteria, but we have verified that the results remain essentially the same if we use 4 or 6 lags.

We start by computing the appropriate bandpass filtered volatility of variable k using the VAR and the vector ε. The spectral density of variable k at frequency ω, $F_k(\omega)$, is given by[10]

$$F_k(\omega) = \frac{1}{2\pi} C_k(e^{-i\omega}) \overline{C_k(e^{-i\omega})}$$

where $C_k(z)$ is the k-th row of the polynomial matrix $C(z)$ and $\overline{C_k(z)}$ denotes the complex conjugate transpose of $C_k(z)$. We have made use of the fact that $\mathbb{E}(\varepsilon\varepsilon') = I$. The volatility of variable k, σ_k^2, over the frequency band $[\underline{\omega}; \overline{\omega}]$ is then given by[11]

$$\sigma_k^2 = \int_\Omega F_k(\omega) \mathrm{d}\omega$$

where $\Omega = \{\omega \in \mathbb{R} \text{ s.t. } \underline{\omega} \leqslant |\omega| \leqslant \overline{\omega}\}$.

Due to the independence of the elements of ε, the spectral density of variable k attributed to each of these elements is[12]

$$G_k(\omega) = \frac{1}{2\pi} \overline{C_k(e^{-i\omega})} C_k(e^{-i\omega})$$

$G_k(\omega)$ is a $(N \times N)$ diagonal matrix whose j-th diagonal element gives the spectral density of variable k at frequency ω generated by the j-th ε. The volatility of variable k over $[\underline{\omega}, \overline{\omega}]$ explained by the ε vector is then given by

$$\Sigma_k \equiv \int_{\omega \in [\underline{\omega}, \overline{\omega}]} G_k(\omega) \mathrm{d}\omega$$

which is a diagonal matrix whose (j, j) element gives the volatility of variable k in the frequency range $[\underline{\omega}, \overline{\omega}]$ that is explained by the j-th ε.

Let as call this element $\sigma_{k,j}^2$. The share of the total volatility of variable k in the band $[\underline{\omega}, \overline{\omega}]$ that is explained by the j-th ε is then given by

$$\Theta_{k,j} = \frac{\sigma_{k,j}^2}{\sigma_k^2}$$

Our objective is to obtain the orthonormal vector q that combines the εs in a way that generates the highest contribution to the volatility of variable k. Such a q solves the problem

$$\begin{aligned} &\max_q \; q' \Theta_k q \\ &s.t. \; q' q = 1 \end{aligned}$$

[10]See Hamilton (1994).

[11]In practice, we define the frequency gain function

$$f(\omega) = \begin{cases} 1 & \text{if } \underline{\omega} \leqslant |\omega| \leqslant \overline{\omega} \\ 0 & \text{otherwise.} \end{cases}$$

which corresponds to the filter gain for the ideal bandpass filter for frequencies $[\underline{\omega}, \overline{\omega}]$ and apply the inverse fast Fourier transform algorithm to the filtered spectral density $\widetilde{F}_k(\omega) = f^2(\omega) F_k(\omega)$.

[12]Note that in order to determine the effects of ε we reversed the ordering between $C_k(e^{-i\omega})$ and $\overline{C_k(e^{-i\omega})}$.

where Θ_k is a diagonal matrix whose j–th element is given by $\Theta_{k,j}$. It follows that q is the eigenvector associated to the largest eigenvalue of matrix Θ_k. This has a similar flavor as the method of identifying a principle component or a factor (e.g., Stock and Watson, 2005), except for the fact that our "factor" targets exclusively the volatility of a particular variable over a particular frequency band.

3 Empirical findings

By construction, any of the shocks we identify represents a one-dimensional cut of the data. Varying the targeted variable and the targeted frequencies allows to consider multiple such cuts of the data. The "anatomy" offered in this paper is a compilation of the conditional comovement patterns revealed by such cuts of the data. This section presents the main findings of this proceedure and discusses their implications for macroeconomic theory.

3.1 The Main Business Cycle Shock: Targeting Unemployment

We start with the shock that targets the volatility of unemployment at the business cycle frequencies, namely the range of 6-32 quarters. Table 1 reports the contribution of this shock to the volatility of various macroeconomic variables in that range (short run) as well over the 80-∞ range (long run). Figure 1 shows the corresponding impulse response functions (IRFs).

Table 1: Variance Contributions of Unemployment Shock

	u	Y	h	I	C	π	R	r	TFP	Y/h	w	wh/Y
Short Run	68.15	59.93	55.99	65.02	20.67	10.70	27.03	15.73	6.02	12.15	5.11	29.96
Long Run	11.85	4.17	8.83	4.84	3.96	12.48	21.09	16.40	4.11	4.05	5.32	5.63

Note: The shock is constructed by targeting unemployment. The first row (Short Run) reports the contribution of this shock to the volatility of the various variables between 6 and 32 quarters, the second row (Long Run) between 80 quarters and ∞. The variables are denoted as follows: $Y =$ GDP, $h =$ hours in the non-farm business sector, $I =$ investment, $C =$ consumption, $u =$ unemployment rate, $\pi =$ inflation rate (GDP deflator), $R =$ nominal interest rate (Federal Funds rate), $r =$ real interest rate (with expected inflation constructed from the VAR), TFP $=$ utilization-adjusted Total Factor Productivity, $Y/h =$ labor productivity, $w =$ real wage, $wh/Y =$ labor share.

What are the main properties of the identified shock?

First, it explains two thirds of the business-cycle volatility in unemployment and investment, nearly as much of that in GDP, and more than one half of that in hours. It also gives rise to a realistic business cycle, with all the aforementioned variables, as well as consumption, moving in tandem. These properties together with those reported in the next subsection justify labeling the identified shock as the "main business-cycle shock."

Second, the identified shock contains little statistical information about the business-cycle

Figure 1: Impulse Response Functions to the Unemployment Shock

Shaded area : 68% HPDI.

variation in either TFP or labor productivity. In particular, although the shock triggers a procyclical response in labor productivity and in TFP, this response is only short-lived and insignificant in the sense that the shock accounts for only about one-tenth of the business-cycle variation in labor productivity and nearly one-twentieth of that in TFP. To interpret this fact, it is useful to note that, as is shown in the Appendix, the identified shock also leads to a significant, short-lived increase in capacity utilization and accounts for more than 50% of its volatility at the business-cycle frequency.

Third, the contribution of the shock to output fades out at long horizons. This finding extends and reinforces the key message of Blanchard and Quah (1989): what drives the business cycle appears to be distinct from what drives output in the longer term. This point is further corroborated by the evidence reported in Subsection 3.3 below.

Fourth, the shock triggers a procyclical, albeit small and delayed, movement in inflation. This invites the interpretation of the identified shock as a demand shock under the lenses of the New Keynesian model. We discuss in detail in Section 3.5 the challenges faced by this interpretation. For now, we note that the identified shock explains only one tenth of the business-cycle variation in inflation, which is comparable to its contribution to TFP and labor productivity—and much lower than its contribution to unemployment and the other macroeconomic quantities.

Fifth, the shock triggers a weak and delayed procyclical movement in the real wage. This echoes the more familiar result that the *unconditional* correlation between real wages and output is small and is consistent with models that feature some form of real wage rigidity. But it could also be that the measured wages are not allocative.

Sixth, the shock triggers a countercyclical response in the labor share for the first few quarters, which is reversed later on. This is essentially the product of the aforementioned responses of the real wage and labor productivity: the labor share coincides with the gap between the real wage and labor productivity. It is also in line with the evidence in Chari, Kehoe, and McGrattan (2007) and elsewhere about the strong cyclicality of the labor wedge. But as it will become clear shortly, the data does not favor theories that tie the variation in the labor wedge to either technology shocks or expectations about future productivity.

Finally, the shock triggers a syncronous procyclical movement in the *real* interest rate. In the Keynesian model, this could result from monetary policy implementing a countercyclical nominal interest rate coupled with unresponsive inflation. But it is also consistent with a neoclassical model in which the boom reflects an increase in the demand for goods today relative to goods tomorrow, which in turn manifests as an increase in the relative price of the former.

3.2 The Main Business Cycle Shock: Targeting Other Quantities

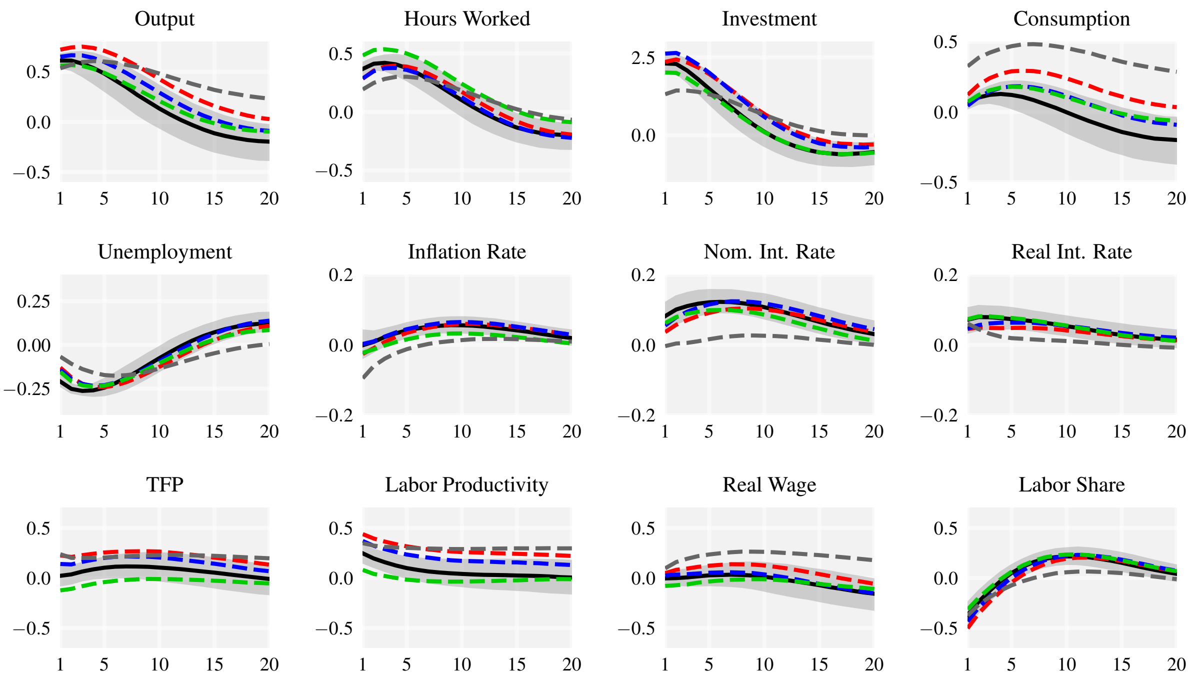
Figure 2 compares the IRFs of the shock that targets the unemployment rate (black line) to the IRFs of the shocks that are identified by targeting the business-cycle volatility of a some other key macroeconomic quantities: GDP (red line), hours (green line), investment (blue line), and consumption (gray line). As is evident from the figure, the IRFs are nearly indistinguishable: targeting any one of these variables seems to give rise to the same shock.

Figure 3 paints a similar picture by considering the scatterplots of the series of innovations corresponding to the shock that targets unemployment against those corresponding to the other shocks. The scatterplots are virtually on top of the 45-degree line, indicating, once again, that all the shocks are essentially same.

These findings explain why we view all these one-shock representations of the data as interchangeable: they all seem to encode the same information, whether in terms of innovations (Figure 3) or in terms of propagation (Figure 2). It is this kind of information that we henceforth refer to as the "main business-cycle shock" in the data.

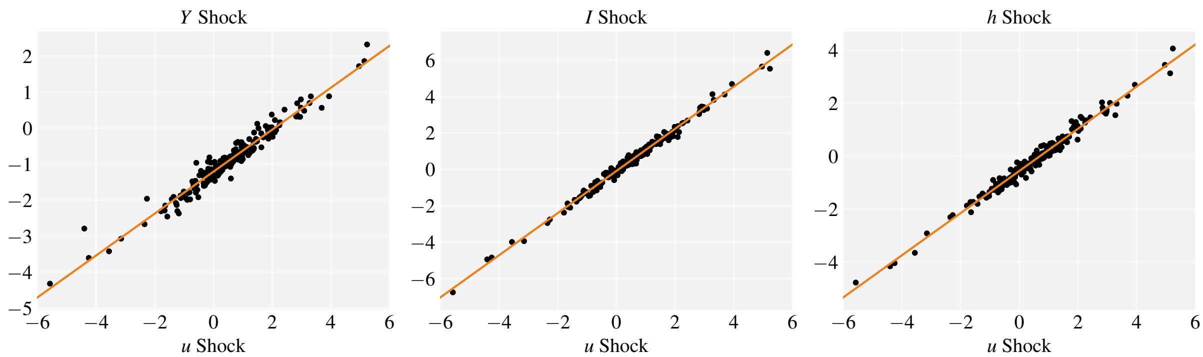
Table 2 turns to variance contributions. Consider unemployment, GDP, hours and investment. The shock that targets *any* of these variables explains between 50% and 80% of the business-cycle volatility in *all* of these variables. This echoes a similar finding from Stock and Watson (2005). That paper uses a different method, namely factor analysis, but finds that a single factor can account for most of the short-run variation in industrial production and employment. The main added value here is, not the corroboration of this result through the use of a different method,

Figure 2: The Main Business-Cycle Shock, IRFs



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

Figure 3: The Main Business-Cycle Shock, Scatterplots



Note: The left panel is the scatter plot of the innovations of the shock that targets GDP (on the vertical axis) against those of the shock that targets unemployment (on the horizontal axis). The remaining two panels repeat this for the shocks that target investment and hours.

but rather the finding that such "singleness" extends to the dynamic comovement patterns of the key macroeconomic quantities, the documentation of these patterns (summarized in Figures 1 and 3), and their use to draw new lessons for macroeconomic theory.

Table 2: The Main Business-Cycle Shock, Variance Contributions

	u	Y	h	I	C	π	R	r	TFP	Y/h	w	wh/Y
u	68.15	59.93	55.99	65.02	20.67	10.70	27.03	15.73	6.02	12.15	5.11	29.96
Y	55.40	78.24	48.87	70.64	36.65	12.49	16.21	7.77	15.65	36.32	8.19	42.96
h	53.21	50.95	70.91	52.51	21.39	7.75	18.67	15.75	5.83	4.37	4.63	26.91
I	56.94	67.79	48.22	81.22	23.69	11.20	22.37	10.53	11.53	25.95	5.55	37.39
C	23.09	42.48	23.51	25.93	62.28	16.84	5.27	6.02	9.01	23.02	11.31	18.74

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-cyle volatility of the variables.

We close this subsection by commenting on the behavior of consumption, which is a bit more subtle. Recall that the measure of consumption in the VAR under consideration excludes spending on durables; the latter is instead included in the measure of investment. With this qualification in mind, note that, as shown in Table 1, the shock that targets unemployment accounts for only 21% of the fluctuations in consumption. And symmetrically, as shown in Table 2, the shock that targets consumption explains only 23% of the fluctuations in unemployment.

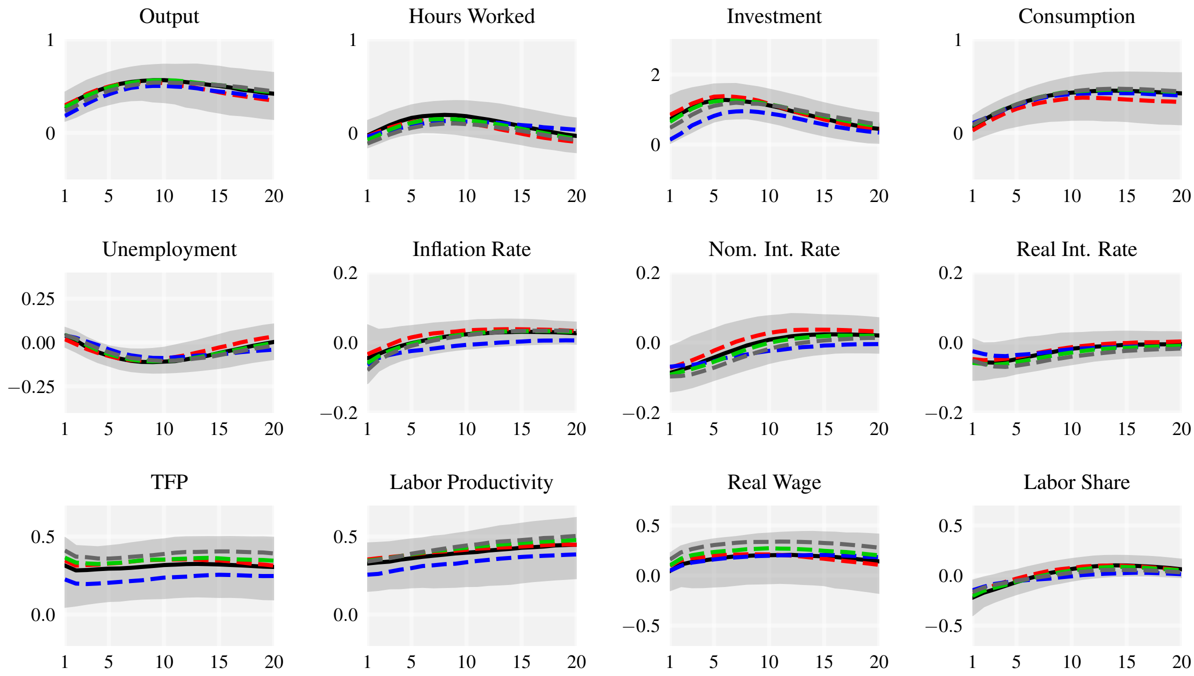
Splitting our measure of investment to its business and household components (see Appendix A.2) refines the picture as follows: the shock that targets unemployment explains 23% of the fluctuations in consumer spending on non-durables and services, 38% of those in consumer spending on durables, and 62% of the fluctuations in gross private domestic investment. And symmetrically, the shock that targets consumer spending on non-durables and services explains 23% of the fluctuations in unemployment; the shock that targets consumer spending on durables explains 38% of the fluctuations in unemployment; and the shock that targets business investment explains 51% of the fluctuations on unemployment.

These findings are consistent with the well-known fact that consumer spending on durables is much more cyclical than spending on non-durables and services. But they also raise an intriguing question. Is the relatively weak relation between our main business cycle shock and consumer spending consistent with a consumer-centric view of the business cycle? Or does the relative stronger relation between the former and investment speak in favor of investment-centric theories, such as those articulated in Justiniano, Primiceri, and Tambalotti (2010) and Caballero and Simsek (2017)? We leave any further investigation of this issue for future research.

3.3 The Short Run vs the Long Run and the Role of TFP

On the basis of Table 1, we claimed that whatever drives the business cycle plays a small role in the long-term movements of economic activity. We now examine the reverse, namely, whether the shock that best accounts for the long-term movements has any bearing on the business cycle. We then probe in greater detail the role played by technology, as proxied by the movements in utilization-adjusted TFP and the relative price of investment at various frequencies and horizons. We finally discuss the implications of our results for theories that attempt to tie the business cycle to news about the future.

Figure 4: Long-Run Shocks



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

Consider the shock that targets the frequencies corresponding to 80-∞ quarters, for any of the following variables: GDP, investment, consumption, TFP, and labor productivity.[13] Figure 4 shows that these shocks are indistinguishable in terms of IRFs. The same picture emerges if we look at the variance contributions of these shocks either in the long term (Table 3) or in the short term (Table 4). This finding is consistent with a single unit-root force, such as a persistent technology shock, driving the long-term volatility in all these variables, and allows us to think of any of these shocks as the "main long-run shock."

[13]Here, we omit the shocks that target unemployment and hours because these variables are stationary. Also, we have verified that the shocks considered here are nearly identical to those identified by a long-run restriction as in Blanchard and Quah (1989): there is no essential difference between the shocks that target the frequency exactly at ∞ (which is what such a long-run restriction does) and the alternatives considered here.

As is evident from Table 4, this shock accounts for less than 15% of the business-cycle volatility in unemployment and hours, and only a little more of that in investment. This is, in effect, the mirror image of the disconnect between the short and the long run seen in the second row of Table 1, which reported the long-run contribution of the main business-cycle shock.

Table 3: Long-Run Shocks, Contributions at Long-Run Frequencies (80-∞ q)

Targeted Variable	Y	I	C	TFP	Y/h
Output	99.15	96.51	99.03	93.71	98.08
Investment	96.57	98.15	96.34	94.49	97.45
Consumption	98.89	96.12	99.10	93.04	97.90
TFP	93.72	93.64	93.53	95.75	95.46
Labor Productivity	98.27	97.22	98.12	96.13	98.99

Table 4: Long-Run Shocks, Contributions at Business-Cycle Frequencies (6-32 q)

Targeted Variable	u	Y	h	I	C	π	R	r	TFP	Y/h	wh/Y
Output	14.26	22.26	12.30	16.67	24.49	11.16	16.63	11.11	16.67	24.53	11.95
Investment	14.82	22.80	12.10	18.40	24.66	12.56	17.36	11.68	21.31	28.40	10.87
Consumption	13.54	21.00	11.55	15.93	23.31	10.92	16.40	10.91	15.90	23.38	11.15
TFP	13.33	18.74	10.63	14.58	23.24	14.71	19.67	12.84	23.59	26.86	8.29
Labor Productivity	13.91	21.27	11.37	15.77	24.08	11.73	17.35	11.63	19.98	26.99	10.47

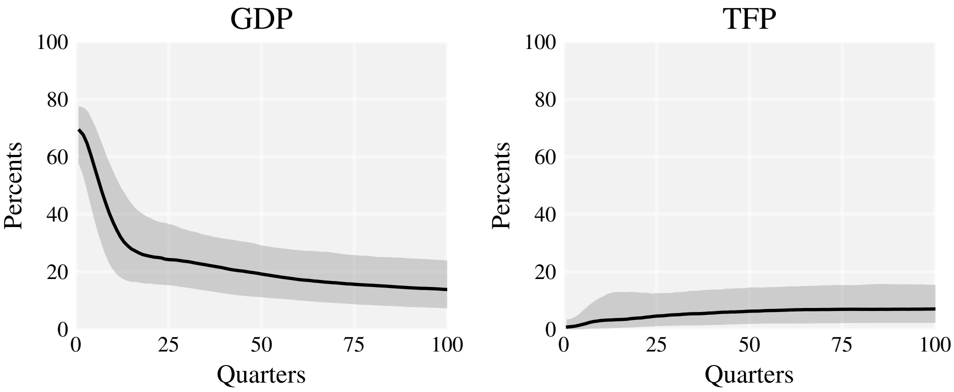
Let us now probe in more detail the role of TFP.[14] In Table 1 we saw that the main business-cycle shock contains little statistical information about both the short and the long-run movements in TFP. In Table 4, we similarly see that the shock that drives TFP in the long-run explains only a small fraction of business-cycle fluctuations in unemployment, hours, and investment. The same is true for the shock that drives TFP in the medium run, in line with the results of Barsky and Sims (2011): as can be seen in Table 15 in Appendix A.5, the shock that targets TFP in the medium run accounts for only 8% of the business-cycle variation in unemployment, despite the fact that this contains almost all the available information about future TFP (namely it accounts for about 80% of the variation in TFP in the medium-run frequencies).

In short, the shock that drives the bulk of the business cycle appears to be disconnected from TFP at *all* frequencies. This is further illustrated in Figure 5, which reports the fraction of the variance of the forecasts of GDP and TFP explained by the shock that targets unemployment. As is evident in this figure, this shock explains more than 50% of the GDP movements over the first two years, but less than than 7% of the TFP movements at *any* horizon.

Let us now relate these findings to those in the literature.

[14]Recall that our measure of TFP is adjusted for utilization, as in Fernald (2014).

Figure 5: Variance Contributions to GDP and TFP



Shaded area: 68% HPDI

First, consider Blanchard and Quah (1989). This work seeks to represent the data in terms of two shocks, a "supply shock" and a "demand shock." To this goal, it runs a VAR on two variables, GDP and unemployment; identifies the supply shock as the shock that accounts for the GDP movements in the very long run (at ∞) and the demand shock as the residual shock; and documents that each one of these shocks accounts for nearly one half of business-cycle volatility in GDP. The additional information contained in our larger VAR reduces the contribution of—our various proxies of—the supply shock to between one tenth and one fifth.

Second, consider Uhlig (2003). This work, too, pursues a two-shock representation of the data. The main differences from Blanchard and Quah (1989) are that it considers a larger VAR and that it uses a different identification scheme: it identifies the two shocks that *jointly* maximize the prediction error variances 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 our finding regarding the disconnect between our main business-cycle shock and TFP at all horizons.[15]

Third, 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—interpreted as TFP news—that accounts simultaneously for the bulk of the short-run movements in stock prices and the bulk of the long-run movements in TFP.[16] The second part of that paper proceeds to argue, with the

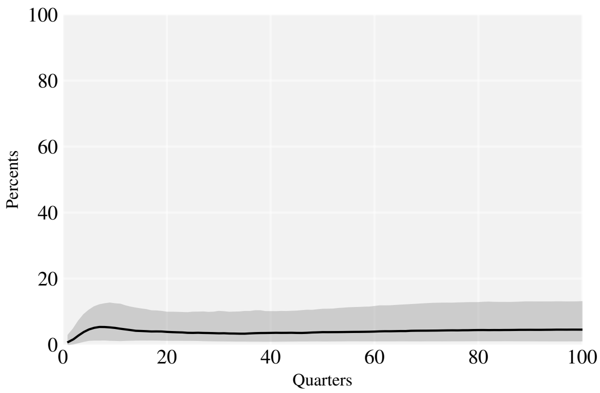
[15] We emphasize that the interpretation offered in Uhlig (2003) was tentative as that paper was not completed. Also note that the approach adopted in that paper allows the identification of the two shocks *together* but does not separate one shock from the other, so the aforementioned interpretation 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.

[16] This is accomplished by using two alternative identification schemes—a short-run restriction that isolates the innovations in stock prices that are orthogonal to current TFP, and a long-run restriction that lets a shock pick all the long-run movements in TFP—and by showing the coincidence of the identified shocks.

help of larger VARs and more delicate identifying assumptions, that such TFP news also account for about 50% of the short-run volatility in hours and total private spending, and up to 80% of that in consumption. In short, TFP news emerges as the main driver of the business cycle. This picture is at odds with the evidence reported in Table 4: the shock that best predicts the long-run movements in TFP accounts for only 10% of the short-run volatility in hours, 14% of that in investment, and 23% of that in consumption. It is also inconsistent with Figure 5, which indicates that the main business-cycle shock itself contains little news about future TFP.[17]

Fourth, consider Ben Zeev and Khan (2015). That paper argues that the main driver of the business-cycle fluctuations in employment is news about investment-specific technology, as proxied by the relative price of investment. If that were the case, one would expect our main business cycle shock to contain substantial predictive power for future movements in the relative price of investment. Figure 6 shows that this is not the case: our main business-cycle shock contains negligible information about the relative price of investment at all frequencies. Similarly, when we consider the shock that best encapsulates the available information about the future movements of the relative price of investment in either the medium or the long run, we find that this shock explains only 7 to 8% of the business-cycle volatility in unemployment.[18]

Figure 6: Variance Contribution to Relative Price of Investment



Shaded area: 68% HPDI

Finally, consider Lorenzoni (2009) where the news about future TFP is contaminated with noise. Furthermore, the noise triggers a business cycle that is orthogonal to past, current and

[17]We believe that the picture painted by Beaudry and Portier (2006) owes much to two elements. The first is that the small, two-variable VAR used in the first part of that paper overstates the news that the short-run movements in stock prices contain about long-run movements in TFP. The second is that the more delicate identifying assumptions made in the second part of that paper could be confounding such news with other shocks. We have corroborated these points by adding the SP500 index to our VAR; verifying that the properties of the main business-cycle shock remain unchanged; and inspecting the properties of the shock that drives the short-run volatility in stock prices. As can been seen in Table 11 in Appendix A.5, this shock explains a small fraction of either the business-cycle fluctuations in the key macroeconomic quantities or the long-run fluctuations in TFP.

[18]These findings obtain from an extended VAR that includes the relative price of investment; see Appendix A.5.

future TFP. Does this mean that noise in this model offers a structural interpretation to the main business-cycle shock in the data? The answer is negative. In this model, the fluctuations in employment are driven almost entirely by shifts in expectations of long-term TFP, which in turn implies that these fluctuations account for a large fraction of the forecastable movements in future TFP—a prediction contradicted by our evidence.

This discussion also highlights how our approach relates to Chahrour and Jurado (2018). This paper shows that, although SVARs may not allow a separate identification of the news and noise components of the beliefs about future TFP, they may allow econometricians to recover the innovations in the expectations of future TFP. In a similar vein, we bypass the aforementioned identification challenge and, instead, address the more basic question of whether the business cycle is tied to the forecasts of future TFP.

3.4 What we have learned so far

On the basis of the empirical findings presented above, we reach the following conclusion.

Tentative lesson. *It is possible to account for the bulk of the business-cycle fluctuations in key macroeconomic quantities—namely unemployment, hours, GDP, investment, and, to a somewhat lesser extent, consumption—using a parsimonious model in which the shock driving the business cycle has the following key properties:*

- *it causes strong positive comovements in the aforementioned quantities;*
- *it is essentially orthogonal to TFP at all horizons*;
- *it is an indicator of the short-run but not of the medium- and long-run outlook.*

As already discussed, these properties are hard to reconcile, not only with the baseline RBC model, but also with a variety of models that tie the business cycle to expectations of productivity and income in the medium- long run. They also speak against models in which financial, uncertainty, or other shocks matter primarily by triggering endogenous procyclical movements in aggregate TFP. Benhabib and Farmer (1994) and Bloom et al. (2018) are notable examples of such models: the former generates such procyclical TFP movements out of animal spirits, the latter out of uncertainty shocks.

By contrast, the data seems consistent with extensions of the RBC model that let shocks trigger strong, procyclical, and transitory movements in the measured labor wedge without commensurate movements in aggregate TFP. Such movements could be the symptom not only of labor-market frictions but also of other real frictions. For example, in Angeletos, Collard, and Dellas (2017) such movements are the byproduct of higher-order uncertainty about the short-term economic outlook; in Arellano, Bai, and Kehoe (2018) they 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.

Last but not least, the data seems consistent with New Keynesian models that attribute the business cycle to the interaction of nominal rigidities with shifts in aggregate demand (provided that the latter do not represent news about future TFP). In the rest of the paper, we discuss the challenges faced by such a structural interpretation of our main business-cycle shock.[19]

This is done in two steps. First, we relate the empirical regularities encapsulated in our anatomy to the predictions of the textbook New Keynesian model (Subsection 3.5). Second, we take a close look at the mechanics and the empirical performance of state-of-the art, medium-scale, DSGE models (Section 4). The first exercise focuses on the predictions of the New Keynesian model regarding the comovement of inflation and real economic activity; the second turns to the comovement of the different macroeconomic quantities. Both exercises lead to the same conclusion: the business cycle in the data is unlike that on display in the dominant paradigm and can instead be understood better within a class of models that allow realistic, demand-driven fluctuations to obtain without a strict reliance on nominal rigidities and Philips curves.

3.5 Inflation

In the New Keynesian framework, demand shocks (e.g., taste, financial or other shocks that affect consumer spending) are able to generate realistic business cycles only when the combination of nominal rigidity with certain monetary policies allows such shocks to trigger sufficiently large deviations from the underlying flexible-price allocations. This is because the latter coincide with the equilibrium allocations of the baseline RBC model, which in turn is unable to generate the empirically relevant comovement patterns in the macroeconomic quantities out of demand shocks. Using the aforementioned deviations is therefore the *only* way to get the right comovements in the New Keynesian model. But such deviations represent movements along the Philips curve, which explains why the comovement of inflation and of real activity is at the core of the model.

From this perspective, the relation between the business cycle and inflation is the litmus test of the New Keynesian model, just as the relation between the business cycle and productivity is the litmus test of the RBC model. We already noted that the connection between the business cycle and inflation is rather weak in the sense that our main business-cycle shock accounts for

[19]There are of course other possibilities which we do not address in this paper, such as the possibility that the business cycle is driven by tax shocks (Mertens and Ravn, 2013). We also do not discuss financial shocks in detail for two reasons: first, such shocks were presumably not as important in our sample (recall that our data stops in 2007 so as to exclude the recent financial crises); and second, such shocks often represent either endogenous TFP fluctuations or demand shocks of the New Keynesian type.

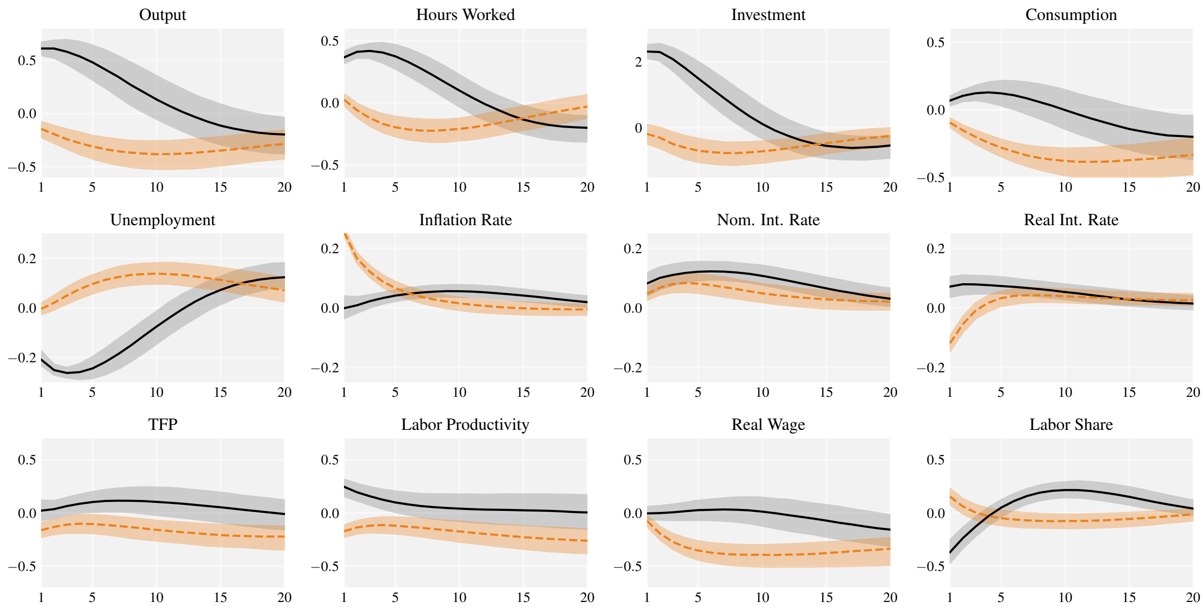
only a small portion of the business-cycle volatility in inflation. We now turn to the shock that makes the maximal contribution to the business-cycle volatility in inflation.

Tables 5 and Figure 7 show the variance contributions of that shock and its IRFs, respectively. To facilitate the comparison of this shock to the main business-cycle shock, we also include the variance contributions and IRFs of the shock that targets unemployment.

Table 5: Inflation vs Unemployment Shock

Target	u	Y	h	I	C	π
Inflation	8.86	8.93	10.01	5.84	19.06	80.78
Unemployment	68.15	59.93	55.99	65.02	20.67	10.70

Figure 7: IRFs to the Inflation and Unemployment Shocks

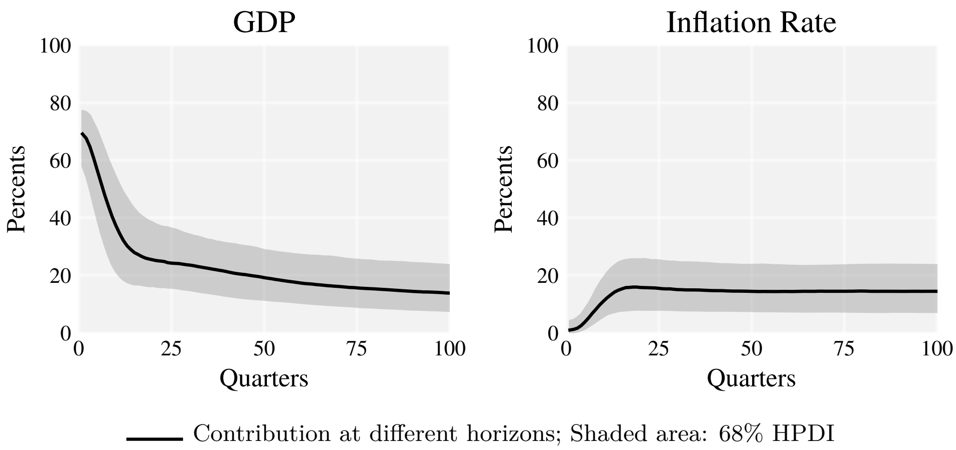


Unemployment Shock; Inflation Shock; Shaded area: 68% HPDI.

The shock that targets inflation looks like a cost-push shock of the New Keynesian type in the sense that it makes inflation and output move in opposite directions. However, this relation, too, is rather weak, in the sense that the shock accounts for only 9% of the business-cycle volatility in unemployment and GDP, although it explains 80% of the volatility in inflation. This is essentially the mirror image of the picture encountered earlier when looking at the inflation contributions of the shocks that targeted the key macroeconomic quantities.

From either perspective, the business cycle therefore appears to be disconnected from the movements in inflation. Figure 8 further illustrates this disconnect by drawing the fraction of the variance of the forecasts of inflation at different horizons explained by the shock that targets unemployment (which may be interpreted as a demand shock): this shock accounts for a very small fraction of the movements of inflation at *any* horizon.

Figure 8: Variance Contribution of Unemployment Shock to GDP and Inflation



As shown in Figure 14 in Appendix A.4, the disconnect survives the purge of real economic activity and inflation from the effect of supply shocks, as proxied by the shocks that account for TFP at the various frequencies. Hence, the disconnect does not seem to be driven by the combination of offsetting "demand" and "supply" shocks.

Last but not least, the same disconnect characterizes the relation between inflation and the labor share, a commonly used proxy of real marginal cost (Galí and Gertler, 1999). As shown in Table 13, the shock that targets the labor share explains 80% of its own business-cycle volatility but only 6% of that of inflation. And symmetrically, the shock that accounts for the bulk of business-cycle variation in inflation contains negligible statistical information about the variation in the labor share (both at the same frequencies and lower frequencies).

In short, the signal-to-noise ratio in inflation vis-a-vis either the real marginal cost, as captured by the labor share, or the output gap, as captured by our main business-cycle shock, is nearly zero. To use an analogy, the NKPC is as successful in accounting for the movements in inflation as the basic asset-pricing model is in accounting for movements in asset prices.[20]

What is more, the disconnect between the business cycle and inflation seen in Figure 8 is comparable to that between the business cycle and TFP seen earlier in Figure 5. In this regard, the failure of baseline New Keynesian model is as significant as that of the baseline RBC model.

We now shift our focus from variance contributions and signal-to-noise ratios to the magnitude of the response of inflation to the main business-cycle shock; think of this as the slope of the Phillips curve. In particular, we show that, although the main business-cycle shock causes

[20]As documented by Campbell and Shiller (1988), innovations in asset returns contain negligible information about future dividends. In the same vein, our evidence points out that the business-cycle innovations in inflation contain negligible information about the corresponding fundamentals. See King and Watson (2012) for complementary evidence.

a positive inflation response (as seen in Figure 9), the magnitude of this response is hard to account for within the New Keynesian model.

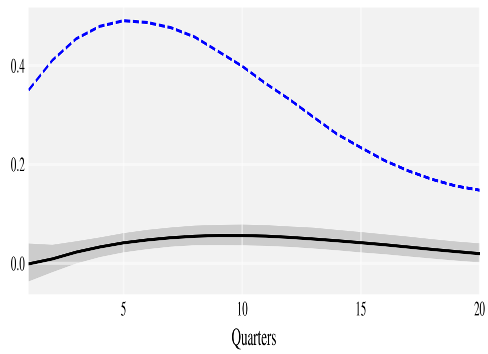
Consider the standard version of the NKPC. This is can stated as follows:

$$\pi_t = \kappa x_t + \beta \mathbb{E}_t[\pi_{t+1}] = \kappa \mathbb{E}_t \left[\sum_{j=0}^{\infty} \beta^j x_{t+j} \right] \tag{1}$$

where π_t is the inflation rate, x_t is the real marginal cost, $\beta \in (0,1)$ is the discount factor, κ is given by $\kappa = (1-\theta)(1-\beta\theta)/\theta$, and θ is the probability of not been able to reset prices. Following common practice, we consider the labor share as a proxy for x_t. It then follows that, if we interpret the main business-cycle shock as a demand shock in the context of the New Keynesian model, we can use the identified IRF of the labor share to that shock in a parametrized version of (1) to obtain the model's prediction of the response of inflation to that shock.

A typical textbook calibration, as in Galí (2008), sets $\theta = 2/3$ (prices are, on average, reset every 3 quarters) and $\beta = 0.99$. With these values, the response of inflation implied by the NKPC is given by the blue dashed line in Figure 9. Clearly, this is enormous relative to that in the data. This illustrates the difficulty the baseline New Keynesian model faces in accommodating the type of demand shock encapsulated in our main business-cycle shock.

Figure 9: The Main Business-Cycle Shock and the NKPC



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

To sum up, the evidence presented here raises two challenges for the New Keynesian model. One, just discussed, regards the small magnitude of the response of inflation to the main business cycle shock. The other, which was discussed earlier, regards the near orthogonality of the forces that drive inflation and those that drive real economic activity.

These challenges are not entirely new. For instance, the weak comovement of inflation and real economic activity is evident, albeit not as pronounced, in the unconditional moments, too. It is also the subject of a large empirical literature on the Phillips curve; see the survey by Mavroeidis, Plagborg-Møller, and Stock (2014).

The New Keynesian literature has sought to bypass these challenges by: (i) assuming that the Phillips curve is much flatter than the one in the textbook version of the model; and (ii) attributing almost all of the variation in inflation to markup or cost-push shocks. However, it is questionable how much flatness of the Philips curve can be supported by the micro-economic evidence on price behavior.[21] Furthermore, the micro-foundations used to support a flat Philips curve do not justify large responses to some shocks and small responses to other shocks. As a result, the literature has attempted to account for the volatility in inflation through markup shocks that, not only look a priori suspect, but also predict implausibly large fluctuations in economic activity under flexible prices.[22]

An alternative hypothesis, which we favor, is that demand-driven fluctuations operate outside the realm of Phillips curves and are compatible with flexible prices. This hypothesis has a long history in Keynesian thinking (e.g., Diamond, 1982; Cass and Shell, 1983) and has recently been revived by the literature cited in the beginning of the Introduction.

4 An Application to Medium-Scale DSGE Models

So far, we have tried to interpret the data through the lenses of parsimonious, textbook-type models that aspire to account for the bulk of the business-cycle variation in real quantities with a single shock/propagation mechanism. This has obvious limitations. If one wishes to account simultaneously for the short- and the long-run movements in real economic activity, one has to add a second shock. If one wishes also to account for inflation, one has to add a third shock. And so on. This can quickly lead to a medium- or even large-scale DSGE models.

The relative advantages/disadvantages of small and large models are well known; we do not wish to review them here. What we wish to do, though, is to illustrate that our method can be deployed to evaluate models of the latter type, too. We also wish to provide additional support for two ideas: (i) that the main business-cycle shock characterized here cannot be easily accounted for by state-of-the-art New Keynesian models; and (ii) that this defect could be due to the exclusion of demand-driven business cycles from the flexible-price core of these models.

[21] This is the subject of a large, ongoing literature on product-level price data and menu-cost models. Although there is no conclusive verdict yet, it is worth noting that the evidence in Bils, Klenow, and Malin (2012) challenges the DSGE practice of attributing a flat Phillips curve to Kimball-like kinked demand curves and strong pricing complementarities. Also note that the gap seen in Figure 9 cannot be accounted for by sticky wages—another core ingredient of the DSGE literature—because the predicted value for inflation has been constructed taking as given the empirical response of the labor share. Finally, the introduction of past-price indexation—which leads to the replacement of the standard version NKPC with the so-called hybrid version—helps generate more sluggishness in the response of inflation but does not close the aforementioned gap, unless it is accompanied by the assumption of a higher price-stickiness.

[22] For instance, the markup shock in Smets and Wouters (2007) is akin to having a joint tax on capital and labor that varies between 6% and 21% (this is the mean estimate of the markup plus/minus two standard deviations).

To these goals, we consider two off-the-shelf DSGE models. One is the New Keynesian model found in Justiniano, Primiceri, and Tambalotti (2010). This is essentially the same model as that in Smets and Wouters (2007) but with more appropriate measures of investment and consumption.[23] We henceforth refer to this model as JPT. The other is the RBC model in Angeletos, Collard, and Dellas (2017), henceforth referred to as ACD. The main differences between JPT and ACD is that the latter has flexible prices and also contains a "confidence shock," namely a shock that helps generate waves of optimism and pessimism about aggregate demand in the short run.[24,25] We use the ACD model, not only because it is ours, but also because we view it us representative of a broader class of models that allows for demand-driven fluctuations under flexible prices.[26]

We take each model in its original form and set its parameters to the values estimated in the respective paper. It is worth noting that these models are comparable in the following respects. First, they both have been estimated with maximum likelihood over the 1960–2007; this means, in effect, that they have been parameterized so as to maximize their fit vis-a-vis the data used in our empirical exercises. Second, each model features a theoretical shock whose estimated contribution to the business-cycle volatility of employment, investment and GDP exceeds 50%: this is the investment-specific demand shock in JPT and the confidence shock in ACD. Finally, these models do equally well in matching the familiar, unconditional business-cycle moments. Notwithstanding all these similarities, as is shown below, these models perform quite differently under the new lens provided by our approach.

For each model, we construct the linear combinations of the theoretical shocks that maximize the business-cycle volatility of GDP, investment, consumption or hours in the model. These objects are meant to be the theoretical counterparts for the shocks we identified in the data. To

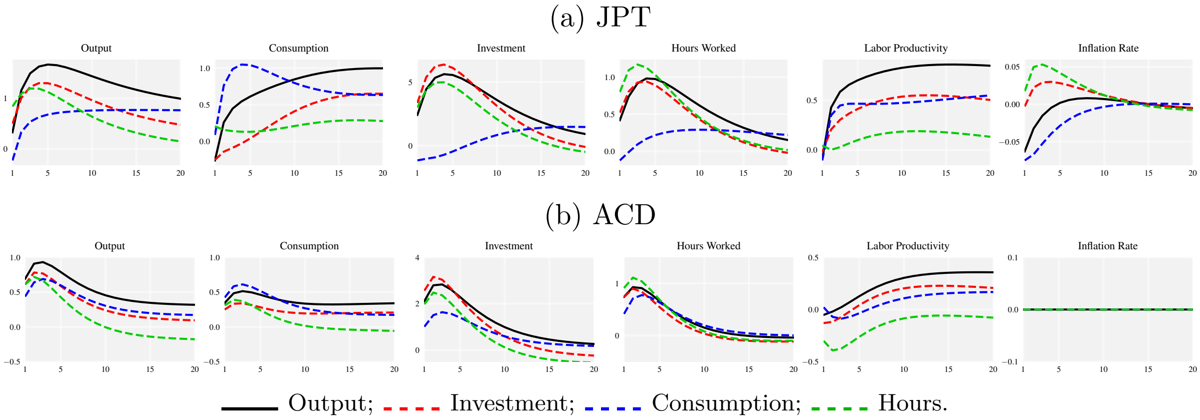
[23]The measure of consumption used in Smets and Wouters (2007) includes expenditure on durables, which is at odds with the specification in the model. Justiniano, Primiceri, and Tambalotti (2010) fix this problem by including such expenditure to the measure of investment, just as we have done both here and in Angeletos, Collard, and Dellas (2017).

[24]ACD treats the variation in confidence as the product of an exogenous shock to higher-order beliefs; recent work by Angeletos and Lian (2017) and Ilut and Saijo (2018) illustrates how such variation can obtain endogenously in response to more conventional shocks, allowing one to think of variation in beliefs as a propagation mechanism rather than as a shock.

[25]There are a few additional differences between ACD and JPT. First, JPT contains increasing returns in production whereas ACD has constant returns; this improves the empirical fit of JPT by letting it generate procyclical movements in labor productivity as a result of demand shocks. Second, due to its assumption of flexible prices and wages, ACD is silent on inflation determination and thus has no use for markup shocks. And third, ACD includes news shocks, as in Barsky and Sims (2012), in order to distinguish between beliefs about the short run (associated with higher-order beliefs) and the long run (associated with news about future TFP).

[26]As noted in the Introduction, this class includes Angeletos and La'O (2013), Angeletos and Lian (2017), Bai, Ríos-Rull, and Storesletten (2017), Beaudry and Portier (2014), Benhabib, Wang, and Wen (2015), Chahrour and Gaballo (2017), Golosov and Menzio (2015), Huo and Takayama (2015), Ilut and Schneider (2014), and Ilut and Saijo (2018).

Figure 10: Comparing Business-Cycle Factors



avoid confusion between these objects and the underlying theoretical shocks, we henceforth refer to the former as “factors” and reserve the term “shocks” for the latter.[27]

The top panel in Figure 10 reports the IRFs of the various factors in JPT and the bottom in ACD. As seen in this figure, the various factors are highly interchangeable in the ACD model, as they are in the data, whereas they are quite distinct in the JPT model. This is 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.

Table 6: Contribution of Factors in Data and Models

	Y	C	I	h	Y/h	π
Output Factor						
Data	78.24	36.65	70.64	48.87	36.32	12.49
JPT	75.15	18.83	63.99	51.64	49.88	3.76
ACD	75.37	44.88	66.52	64.07	8.62	0.00
Investment Factor						
Data	67.79	23.69	81.22	48.22	25.95	11.20
JPT	52.06	12.32	92.48	53.69	19.05	2.38
ACD	57.69	19.13	86.34	60.41	10.71	0.00
Consumption Factor						
Data	42.48	62.28	25.93	23.51	23.02	16.84
JPT	11.85	61.83	5.79	3.54	22.67	9.06
ACD	43.61	78.53	22.30	43.30	4.42	0.00
Hours Factor						
Data	50.95	21.39	52.51	70.91	4.37	7.75
JPT	50.87	0.96	60.03	79.64	2.67	6.60
ACD	57.67	37.11	58.31	89.69	29.38	0.00

A similar picture emerges from Table 6, which compares, one by one, the empirical factors to their theoretical counterparts in terms of variance contributions. In particular, consider the

[27]Clearly, our “factors” should not be confused with those in dynamic factor analysis.

investment factor. In JPT, this factor explains 92% of the business-cycle volatility in investment versus 12% for consumption. In the data, the corresponding numbers are 81% and 23%. And in ACD, they are 86% and 19%. This illustrates that the investment factor in JPT is too "specialized" relative to its counterpart in either the data or ACD. The same applies to the consumption factor. This overspecialization is problematic because the business cycle in the model looks different depending on the viewing angle adopted (i.e., which variable we target), whereas this is not the case in the data.

We now shed light on this result as well as on the mechanics of the models by doing a decomposition of the factors in terms of the underlying theoretical shocks. In Table 7 we calculate, for each model, the contribution of each theoretical shock to the part of the business-cycle volatility of the targeted variable that is accounted by the corresponding factor. This reveals the effective weights of the various shocks in each factor.

Table 7: Decomposition of Factors into Model Shocks

	JPT				ACD	
Factor	A shock	I shock	C shock	other	confidence	other
y	31%	66%	1%	2%	88%	12%
i	0%	99%	0%	1%	80%	20%
c	33%	1%	65%	1%	93%	7%
h	0%	96%	2%	2%	99%	1%

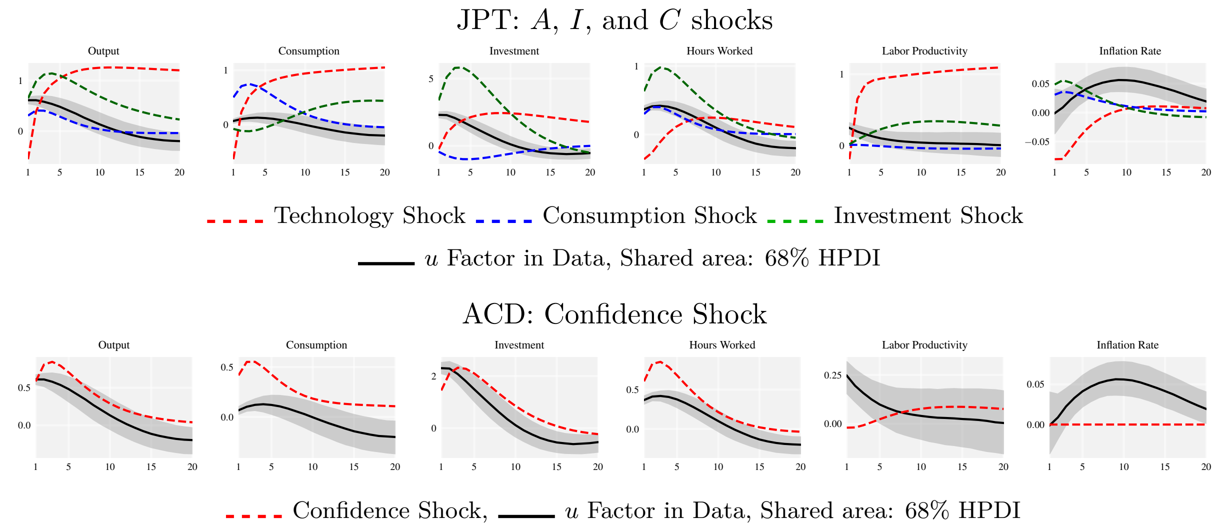
Note: In JPT, "A shock" is a permanent technology shock, "I shock" is a transitory investment-specific demand shock, "C shock" is a transitory discount-factor or consumer-specific demand shock, and "other" includes a monetary policy shock and shocks to price and wage markups. In ACD, "confidence" is a transitory shock to higher-order beliefs, which triggers waves of optimism and pessimism about aggregate demand in the short run, and "other" includes both transitory and permanent technology shocks, news shocks, and the same kind of investment- and consumption specific shocks as those in JPT.

Let us first consider the JPT model. In this model, the investment and hours factors are both accounted almost fully ($> 95\%$) by the investment-specific shock. By contrast, the consumption factor is explained by the combination of two other shocks: the discount-factor shock (65%) and the technology shock (32%). And the GDP factor is explained in part by the investment-specific shock (66%) and in part by the technology shock (30%). The different factors are therefore different mixtures of three theoretical shocks: the technology shock, the investment-specific shock, and the discount-factor shock.

To understand why this feature is responsible for the non-interchangeability of the factors seen in the top panel of Figure 10 we need to combine the above decomposition with the IRFs of the various shocks. The latter are shown in the top panel of Figure 11. Clearly, the three shocks generate distinct co-movement patterns. Furthermore, none of these shocks alone looks like the main business-cycle shock in the data. And most crucially, neither the investment-specific demand shock (which is the main driver of investment and hours) nor the consumption-specific demand shock (which is the main driver of consumption) generates a positive co-movement between consumption and investment in the short run.

The decomposition documented in Table 7 together with the IRFs seen in Figure 11 explain why the model in JPT cannot replicate the *conditional* co-movement patterns revealed by our business-cycle anatomy. This is despite the fact that this model performs very well in the domain of *unconditional* business-cycle moments. In our view, this illustrates a key weakness of the state of the art: not only the specific model under consideration, but also a diverse set of models such as those found in Blanchard, L'Huillier, and Lorenzoni (2013), Jermann and Quadrini (2012), Schmitt-Grohe and Uribe (2012) and Bai, Ríos-Rull, and Storesletten (2017), appear to lack the type of shock and/or propagation mechanism captured by our empirical findings.

Figure 11: Main Business-Cycle Shock in Data vs Theoretical Shocks in JPT and ACD



Consider next the model in ACD. In this model, all the factors are largely driven by one and the same shock, the confidence shock. As explained in more detail in Angeletos, Collard, and Dellas (2017), this shock represents a shift in higher-order beliefs, helps capture waves of optimism and pessimism about the short-term economic outlook, and rationalizes a joint movement in the measured labor and capital wedges. But what is key for the present purposes is the observation, evident in the bottom panel of Figure 11, that this shock is very similar to the main business-cycle shock in the data, in terms of co-movements and relative volatilities. This explains why the estimation of the ACD model favors this shock over the alternatives and also why the factors in that model are as interchangeable as those in the data.

The exercise conducted above relies on constructing the linear combinations of the model's shocks that contribute the most to the predicted volatility of certain variables. This procedure seems ideal for revealing the theoretical comovement properties of each model. Another advantage is that its implementation does not depend on the stochastic dimension of the model under consideration: it can be conducted even if the model has fewer shocks than the variables in our VAR (as it is indeed the case here). One may nevertheless be concerned that this procedure fails to take into account sampling uncertainty. We address this issue in Appendix A.6 by conducting a Monte Carlo exercise: we use each model to generate a large number of artificial time series, we run exactly the same VAR on the data and on the artificial time series, and we compare the median IRFs obtained from the models to those in the data.[28] The picture that emerges from this variant exercise is consistent with the one painted here.

What is the bottom line? Our findings do not have to be read as evidence of the superiority of our own model over those considered in the New Keynesian literature; each framework has its own strengths and weaknesses.[29] We nevertheless hope that the exercise offers a clear illustration of the following points. First, our characterization of the data can be useful in the context of small and large models alike. Second, even state-of-the-art DSGE models appear to lack the kind of comovements/propagation mechanism encapsulated in our empirical findings. And third, the recent literature that aims at disentangling demand-driven business cycles from nominal rigidities and Philips curves holds the promise for rectifying this problem.

5 Conclusions

We have proposed a strategy for dissecting the macroeconomic time series and guiding macroeconomic theory. The strategy involves using a VAR to construct a variety of shocks, each of which maximizes the volatility of a particular individual variable at particular frequencies. The constructed shocks, which may or may not have direct theoretical counterparts, help reveal certain conditional co-movement patterns in the data.

On the basis of this "anatomy" of the data, we argued that the bulk of the business-cycle volatility in the key macroeconomic quantities can be accounted for by essentially the same

[28] This exercise is similar to those conducted in, inter alia, Chari, Kehoe, and McGrattan (2008) and Christiano, Eichenbaum, and Vigfusson (2007). As explained in Appendix A.6, it requires two modifications: first, we drop unemployment and labor productivity from the VAR; first, we augment ACD with a mechanical model for inflation. These modifications are necessary in order to be able to run exactly the same VAR on the data and two models.

[29] For instance, the New Keynesian framework is, naturally, better suited for studying monetary policy. Furthermore, JPT connect their estimated shock to empirical proxies of the level of the financial friction faced by firms, whereas ACD lack such independent evidence. Having said that, the survey evidence reported in Bachmann and Zorn (2018) seems to corroborate a core aspect of the mechanism in ACD, namely that investment is driven by expectations of demand rather than by shocks to the cost of financing or other costs.

shock. This justifies a shift of emphasis from medium-scale models with multiple specialized shocks towards parsimonious models that contain a dominant, even single, driving force. It also provides a set of conditional properties that the theoretical IRFs of such a model ought to display in order to be empirically successful.

We then argued that many existing theories fail to pass this test. In particular, the evidence seems to speak against theories that emphasize any of the following forces: technology shocks; financial and other shocks that matter primarily by affecting the concurrent level of aggregate TFP; shifts in expectations about future TFP and the medium- to long-run productivity prospects of the economy; and demand shocks that operate through a Phillips-curve mechanism.

We finally argued that our empirical strategy can be used, not only to guide the construction of small models, but also to evaluate the performance of medium-scale models. In particular, we used a representative example from the New Keynesian DSGE literature to illustrate how models that perform very well along familiar dimensions—such as the matching of unconditional business-cycle moments or out of sample forecasting—may nevertheless perform relatively poorly when inspected through the lenses of our approach. Despite all the bells and whistles, such models still lack the kind of driving force, or propagation mechanism, that seems to underly the co-movement of the key macroeconomic quantities in the data.

This failure suggests that these models suffer from an important mis-specification. In our view, this failure derives to a large extent from the fact that the flexible-price core of these models is problematic to start with, in the sense that this core is itself unable to accommodate the kind of non-inflationary demand shock we have uncovered with our empirical strategy. It is this feature of the existing paradigm that forces one to conceptualize demand shocks as movements along a Philips curve, thus also leading to a number of empirical "puzzles" such as the missing disinflation of the Great Recession.

There is now a growing literature that attempts to accommodate demand-driven business cycles without nominal rigidities and Phillips curves. We hope that the characterization of the data performed in the present paper will not only encourage further research on this front but also serve as a useful diagnostic test of the empirical potential of such attempts.

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A Appendices

A.1 The 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 8 and 9 describe the original data and the transformations used in our VARs. Table 10 reports the raw (unconditional) correlations over the business-cycle frequencies.

Table 8: 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 Employment	CE16OV	M	Ave
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 9: 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)`
Real Wage	`W=log(PRS85006173/OPHNFB)`
TFP	`TFP=log(cumulative sum (DTFPu/400))`
Construction of IRFs:	
Total Labor Productivity	`YSH=Y-H`
Real Interest Rate	`r=R-`$\mathbb{E}[\pi']$

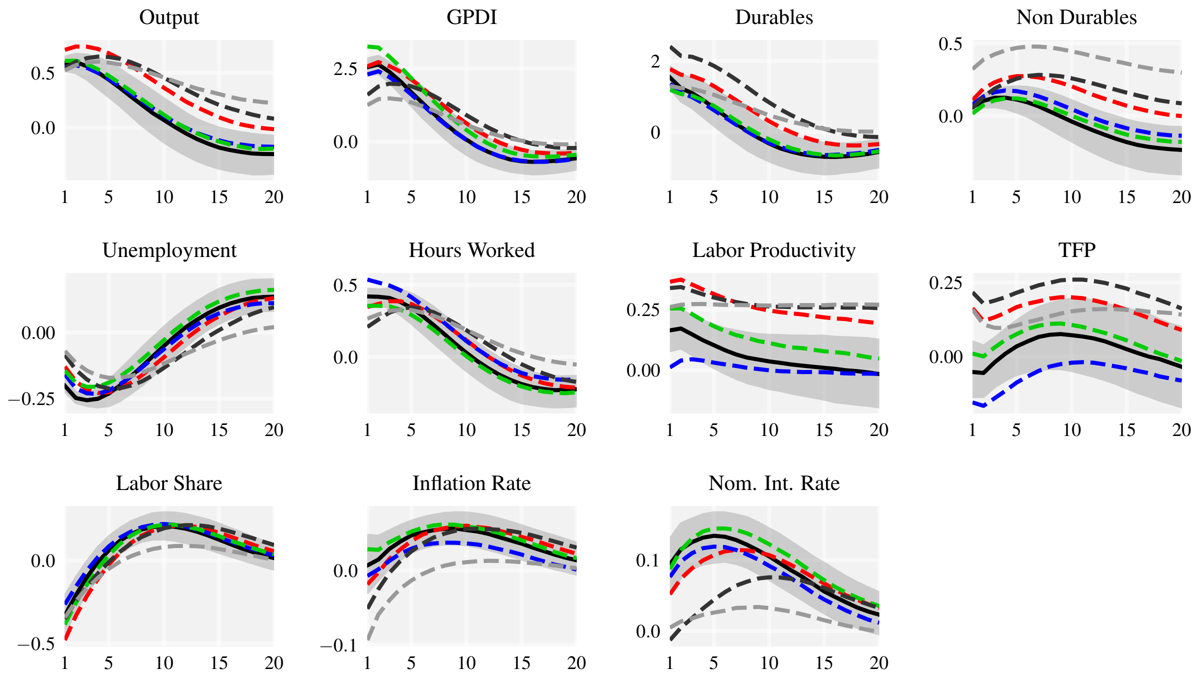
Table 10: Raw Correlations

	Y_t	C_t	I_t	h_t	u_t	$w_t h_t / Y_t$	Y_t / h_t	w_t	R_t	π_t	r_t
Y_t	–	0.85	0.95	0.88	-0.89	-0.21	0.55	0.40	0.36	0.22	0.32
C_t	0.85	–	0.74	0.85	-0.79	0.02	0.31	0.36	0.40	0.33	0.29
I_t	0.95	0.74	–	0.84	-0.85	-0.27	0.57	0.35	0.24	0.09	0.27
h_t	0.88	0.85	0.84	–	-0.93	0.01	0.18	0.20	0.51	0.34	0.44
u_t	-0.89	-0.79	-0.85	-0.93	–	-0.05	-0.21	-0.27	-0.62	-0.43	-0.51
$w_t h_t / Y_t$	-0.21	0.02	-0.27	0.01	-0.05	–	-0.51	0.39	0.35	0.41	0.12
Y_t / h_t	0.55	0.31	0.57	0.18	-0.21	-0.51	–	0.60	-0.38	-0.35	-0.24
w_t	0.40	0.36	0.35	0.20	-0.27	0.39	0.60	–	-0.08	0.01	-0.14
R_t	0.36	0.40	0.24	0.51	-0.62	0.35	-0.38	-0.08	–	0.76	0.77
π_t	0.22	0.33	0.09	0.34	-0.43	0.41	-0.35	0.01	0.76	–	0.16
r_t	0.32	0.29	0.27	0.44	-0.51	0.12	-0.24	-0.14	0.77	0.16	–

A.2 Separating Consumer Durables and Business Investment

Figure 12 and Table 11 revisit our results after splitting our measure of investment to its business and consumer components, namely Gross Private Domestic Investment and Personal Consumption Expenditure on Durables. Clearly, our results are not seriously affected by this change of specification. A single shock can still account for the bulk of the business-cycle fluctuations in the key macroeconomic quantities, and this shock remains essentially orthogonal to both TFP and inflation.

Figure 12: IRFs



u; Y; h; $GPDI$; C^{D}; $C^{\text{ND+S}}$; Shaded area: 68% HPDI.

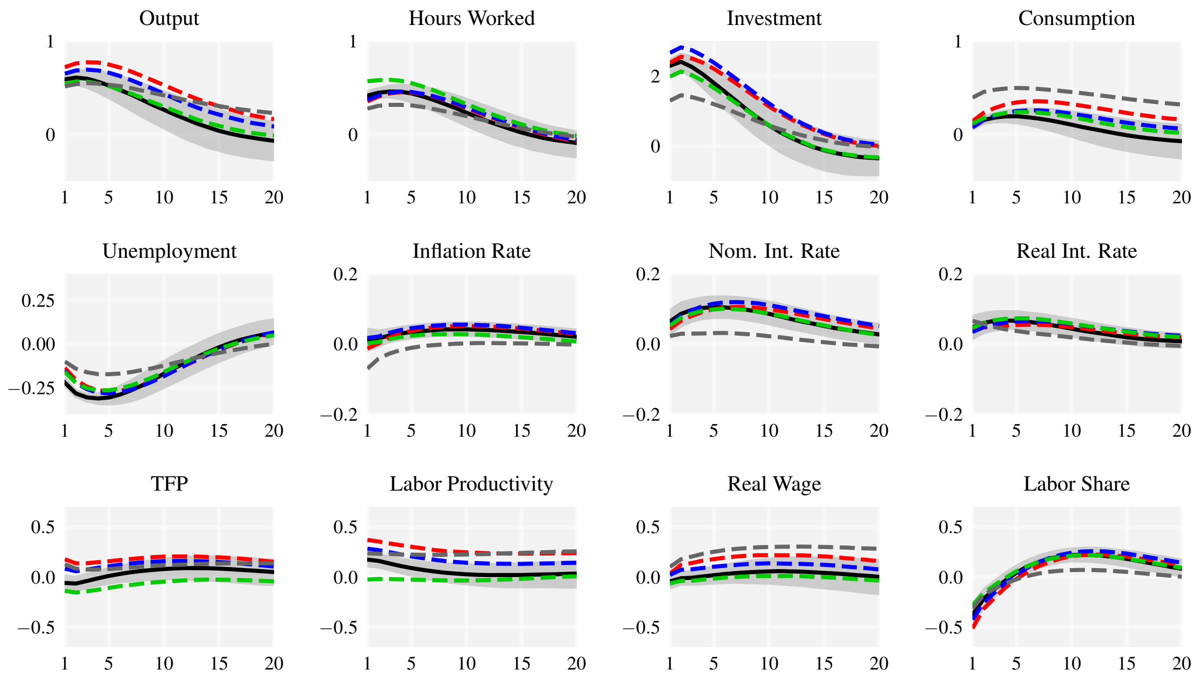
Table 11: Variance Contributions

	u	Y	h	I	C^{D}	$C^{\text{ND+S}}$	π	R	r	TFP	Y/h	w	wh/Y
u	66.50	58.20	55.53	61.68	37.60	23.34	11.42	31.61	19.34	6.75	10.15	5.00	27.19
Y	53.21	76.77	48.39	63.51	48.68	36.12	11.98	19.71	10.60	8.73	35.49	9.01	40.63
h	54.77	52.46	66.79	53.86	31.23	25.68	8.14	26.43	19.19	9.81	3.37	4.28	23.37
$GPDI$	51.33	58.86	45.60	81.66	30.74	19.62	10.52	32.84	17.99	6.62	18.95	4.99	31.67
C^{D}	41.31	54.53	35.43	38.09	71.15	28.61	14.77	10.79	3.85	11.61	28.55	10.53	27.93
$C^{\text{ND+S}}$	23.53	41.42	26.74	21.36	25.56	61.97	14.73	5.52	6.68	4.12	18.15	11.44	17.89
TFP	2.33	4.77	5.84	2.42	6.95	3.62	4.35	4.49	9.05	81.95	35.77	23.58	3.15
π	11.09	9.12	11.41	4.78	14.48	19.05	79.81	14.34	17.91	3.92	3.62	14.95	4.25

A.3 Extending the Sample Period

Figure 13 and Table 12 repeat our anatomy for the extended sample 1960Q1-2015Q4. As can be seen both from the figure and the table, our main results survive as we extend the sample to include the Great Recession period. In particular, the same disconnect with inflation and TFP obtains.

Figure 13: IRFs



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

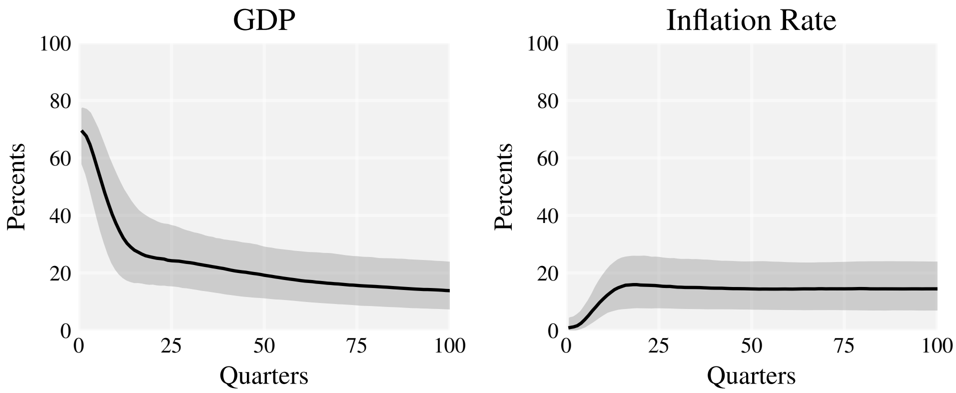
Table 12: Variance Contributions

	Y	h	I	C	u	π	R	r	TFP	Y/h	w	wh/Y
u shock	55.69	50.17	63.44	21.08	68.89	5.29	20.69	13.92	5.69	9.68	3.32	28.96
Y shock	79.02	45.77	69.50	35.84	51.52	8.00	16.37	8.87	6.28	32.23	7.18	41.46
h shock	48.37	69.91	51.78	23.16	49.04	3.94	18.39	14.03	8.17	2.56	2.90	20.71
I shock	66.98	46.61	82.06	23.48	55.69	6.85	20.97	11.01	4.42	20.34	4.06	35.87
C shock	35.98	21.52	22.51	64.90	19.55	7.75	3.88	7.71	2.10	12.50	9.35	11.79
TFP shock	4.66	6.56	3.18	3.80	3.02	5.01	4.89	9.74	86.26	33.25	26.46	2.29
π shock	5.97	5.91	3.89	12.94	5.36	82.25	13.01	16.87	2.97	2.83	11.85	1.93

A.4 Inflation, Supply Shocks, and the Labor Share

Figure 14 revisits Figure 8 after purging the effects of the shocks that account for both the short- and the long-run movements in TFP. Table 13 compares the shocks that target, respectively, inflation and the labor share at the business-cycle frequencies.

Figure 14: The Business Cycle and Inflation, After Purging the Effects of TFP



Shaded area: 68% HPDI

Table 13: Unemployment Shock versus Labor-Share Shock

	π	wh/y
Inflation	80.78	4.70
Labor share	5.95	79.04

A.5 An Extended VAR

The VAR is extended to include data on stock prices (SP), the volatility of asset markets (Vol), the capacity utilization rate (z) and the relative price of investment (p_{inv}). Stock prices are measure by the nominal SP500 index, as downloaded from `http://www.econ.yale.edu/~shiller/data.htm`, averaged to obtain quarterly data and deflated by the GDP price deflator. The volatility index is borrowed from Bachmann, Elstner, and Sims (2013) and is the same as that used in Bloom (2009). The utilization rate and the relative price of investment are borrowed from Christiano, Trabandt, and Walentin (2010).

As can be seen in Table 14, the results reported in the main text are robust to the introduction of these variables. The following additional observations can also be made. First, the utilization shock is another facet of our main business-cycle shock: it is similar to the unemployment, hours, GDP and investment shocks both in terms of IRFs and variance contributions. Second, the shock that drives the relative price of investment at the business-cycle frequencies accounts for a small fraction of the corresponding variation in unemployment and the other key macroeconomic quantities. And third, the same applies to asset-market volatility, contradicting the tight relation between the latter and the business cycle suggested by Bloom (2009) on the basis of a smaller VAR. Finally, Table 15 complements Figure 5 and 6 in the main text by showing that the shocks that drive either TFP or the relative price of investment in either the medium run or the long run account for a small fraction (typically less than 10%) of the business cycle volatility in unemployment and the other key macroeconomic quantities.

Table 14: Extended VAR, Short-Run Contributions of Short-Run Shocks

	u	Y	h	I	C	π	R	r	TFP	Y/h	w	wh/Y	P^i	z	SP	$Vol.$
u shock	64.41	54.85	50.41	54.49	25.07	15.89	42.05	24.48	6.88	13.82	4.58	24.59	10.52	54.28	9.77	12.67
y shock	52.91	67.63	43.77	57.64	27.99	15.48	23.53	11.66	16.95	35.19	5.67	34.29	10.96	47.46	9.32	10.28
h shock	50.88	47.12	60.63	47.92	25.11	11.30	44.14	32.91	4.26	5.72	5.04	16.24	10.57	50.31	9.00	10.19
i shock	54.16	59.09	44.77	66.09	19.47	14.70	30.67	15.75	10.70	24.62	4.23	31.66	10.27	52.21	10.25	13.88
c shock	25.29	34.95	25.40	21.41	55.61	17.01	16.36	9.44	10.92	15.54	9.57	11.58	9.28	23.34	13.63	6.60
z shock	54.38	50.39	49.48	53.38	23.95	19.68	49.27	27.32	4.85	10.36	5.22	18.38	12.78	64.26	11.36	10.27
π shock	10.72	10.70	12.74	6.10	17.98	67.15	15.78	12.18	5.67	4.71	10.69	4.48	5.85	14.20	10.31	4.97
TFP shock	6.94	15.22	4.18	8.41	9.80	13.71	4.59	9.58	81.96	49.72	30.00	8.03	5.25	6.55	6.56	2.58
p_{inv} shock	8.26	8.42	8.34	8.31	6.40	4.73	12.83	8.53	1.83	3.36	1.78	2.54	72.43	9.45	3.02	2.22
SP shock	15.18	13.76	17.23	15.53	15.60	9.47	8.72	4.11	4.84	3.97	8.63	10.11	14.71	13.70	75.93	27.84
Vol shock	11.44	7.48	12.50	12.41	5.02	4.19	7.65	10.07	3.64	4.37	3.64	9.31	6.77	8.95	25.45	81.64

Note: p_{inv}: relative price of investment, z: capacity utilization, SP: stock prices as measured by the SP500 Index, $Vol.$: asset market volatility as measured by VIX. All other variables as in Table 1. Different rows correspond to different shocks and each of the shocks is identified by targeting the volatility of corresponding variable at the business-cycle frequencies.

Table 15: Extended VAR, Short-Run Contributions of Medium- and Long-Run Shocks

	u	Y	h	I	C	π	R	r	TFP	Y/h	w	wh/Y	P^i	z	SP	$Vol.$
Part I: short-run contributions of shocks that drive the long run																
TFP shock	8.29	9.70	9.05	11.67	8.07	7.79	6.54	8.27	10.36	9.70	11.61	8.15	7.72	6.47	20.53	10.95
p_{inv} shock	7.27	8.17	8.63	9.91	7.89	7.84	5.87	7.44	9.96	7.09	12.44	6.93	8.26	5.86	21.42	11.87
Part II: short-run contributions of shocks that drive the medium run																
TFP shock	10.22	18.80	6.35	13.34	8.78	13.66	6.73	10.56	65.17	52.99	28.26	9.77	4.43	7.31	8.45	5.37
p_{inv} shock	8.39	9.49	7.66	9.75	7.24	5.50	7.53	6.09	10.20	10.14	9.33	7.99	39.33	7.22	19.58	11.16

Note: Different rows correspond to different shocks and each of the shocks is identified by targeting the volatility of corresponding variable either in the long run ($80-\infty$ quarters, Part I) or in the medium run ($32-80$ quarters, Part II).

A.6 Running the Same VAR on Real and Artificial Model Data

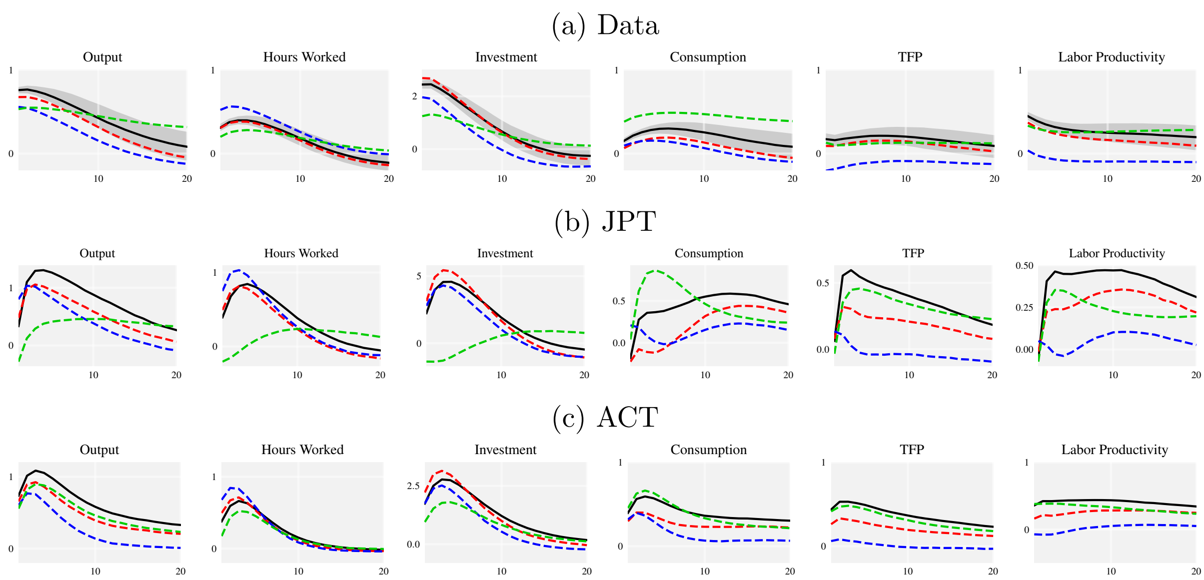
In this section, we rely on Monte Carlo simulations to explore the ability of the JPT and the ACD model to account for the main business-cycle shock in the data. Both models have a stochastic dimension smaller than that of our benchmark VAR. We therefore first rerun our benchmark exercise on a restricted 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 15, 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.[30] 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). 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 15 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.

[30] 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.

Figure 15: Main Business-Cycle Shock



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