IS THERE A SINGLE SHOCK THAT DRIVES THE MAJORITY OF BUSINESS CYCLE FLUCTUATIONS?

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Is There a Single Shock that Drives the Majority of Business Cycle Fluctuations?*

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Abstract

I estimate the set of models in which one shock drives the majority of business cycle fluctuations. This shock explains the bulk of the long-run variation in the relative price of investment and a significant share of that in TFP and features a boom-bust behavior in the late 1990s-early 2000s period. Based on theory and the common view that the late 1990s-early 2000s episode was driven by overly optimistic expectations about information and communications technology which were thereafter revised downwards, the business cycle shock can be interpreted as a news shock about a general purpose technology represented by investment-specific technology.

JEL classification: E32

Keywords: Business Cycles, Business Cycle Shock, General purpose technology, Investment-specific technology news shocks

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1 Introduction

What is the source of business cycles? This question has been the center of attention for macroeconomists for decades but has nevertheless remained a source of debate and disagreement. The list of potential business cycle shocks that have been studied by the macroeconomics literature is quite long. A considerable part of this list pertains to technology related shocks: total factor productivity (TFP) shocks (see, e.g., Kydland and Prescott (1982), Gali (1999), and Basu et al. (2006)); news shocks about future TFP, i.e., shocks that portend future changes in TFP (see, e.g., Beaudry and Portier (2006) and Barsky and Sims (2011)); investment-specific technology (IST) shocks (see, e.g., Greenwood et al. (1988), Fisher (2006), and Justiniano et al. (2010)); and news shocks about future IST (see, e.g., Ben Zeev and Khan (2015) and Ben Zeev (2018)).[1] In recent years researchers have also explored shocks that erroneously move expectations about technology, termed noise or sentiment shocks (see, e.g., Lorenzoni (2009), Blanchard et al. (2013), Angeletos and La'O (2013), and Forni et al. (2017a,b)). And the recent Great Recession has expectedly spawned research on credit supply shocks (see, e.g., Gilchrist et al. (2009), Jermann and Quadrini (2012), Gilchrist and Zakrajšek (2012), and Christiano et al. (2014)).[2]

What This Paper Does. In general, all of the above-cited works take the approach of identifying a shock of interest and then examining its potential role as a business cycle driver. I take a different, more agnostic approach whose aim is to inform us about the existence and nature of the driving force behind business cycles without needing to identify, ex-ante, any shock. This is done by proposing and implementing a Bayesian VAR-based approach that estimates the set of

[1] From a theoretical perspective, Jaimovich and Rebelo (2009) develop a structural modeling framework capable of generating expansionary TFP and IST news shocks. In the context of an estimated DSGE model, Schmitt-Grohé and Uribe (2012) study the role of news shocks to various fundamentals and find that anticipated shocks explain about half of economic fluctuations.

[2] Numerous works have also studied various policy shocks, both on the monetary side (see, e.g., Sims (1980), Christiano et al. (1999), Romer and Romer (2004), Bernanke et al. (2005), and Uhlig (2005)) as well as on the fiscal side (see, e.g., Blanchard and Perotti (2002), Mountford and Uhlig (2009), Romer and Romer (2010), Ramey (2011), Auerbach and Gorodnichenko (2012, 2013), Mertens and Ravn (2013), and Ramey and Zubairy (2017)). Moreover, uncertainty shocks (second moment shocks) have also received increased attention recently (see, e.g., Bloom (2009), Gilchrist et al. (2014), Jurado et al. (2015), Baker et al. (2016), Caldara et al. (2016), and Bloom et al. (2018)). For a much more comprehensive and detailed review of business cycle studies, the reader is referred to Ramey (2016).

models in which one shock produces business cycle comovement and drives the majority of business cycle fluctuations. Then, I examine this set of models and search for common characteristics that can be informative about the nature of the business cycle shock. This exercise enables me to structurally pin down the type of shock at hand based on macroeconomic theory as well as narrative information from the large macroeconomic event of the late 1990s and early 2000s boom-bust period.

In particular, via estimation of a Bayesian VAR that includes a number of real aggregates, TFP, the relative price of investment (henceforth RPI), inflation and interest rates, I first compute all of the models in which one shock raises output, hours, consumption, and investment on impact and explains over 50% of these real aggregates' business cycle variation. Then, I examine the common features of this shock and find that it encompasses two robust characteristics: *i*) it drives the bulk of the long-run variation in RPI and a significant share of that in TFP, reducing the former and raising the latter; and *ii*) it behaves in a boom-bust manner in the late 1990s and early 2000s period, exhibiting significant positive realizations in the former period while experiencing negative realizations in latter period. The first characteristic allows to determine that the shock can be reasonably interpreted as a general purpose technology (GPT) shock represented by either an unanticipated IST shock or an IST news shock as macroeconomic theory implies that IST is the sole source of the long-run variation in RPI.[3,4] The second characteristic permits me to interpret the shock as an IST news shock given the common view by economists that the late 1990s

[3]The concept of GPT has been pioneered in Bresnahan and Trajtenberg (1995) who defined it as technology characterized by the potential for pervasive use in a wide range of sectors and which is expected to bring about and foster generalized productivity gains as it evolves and advances. Information and communications technology (ICT) is commonly considered to constitute a GPT and, since it is an important driver of IST, it is straightforward to view IST as a GPT. Empirical evidence is consistent with the GPT-view of ICT and the associated relation between ICT growth and delayed TFP gains (see, e.g., Basu and Fernald (2007)).

[4]If one allows for IST to be driven by both unanticipated IST shocks as well as IST news shocks, it can be deduced that these two shocks drive the long run variation in RPI. (The reader is referred to section 2.1 for a depiction of the general relation between RPI and IST, as implied by macroeconomic theory, where it is also explained why it is plausible to make the assumption that IST is the sole source of the log-run variation in RPI.) Hence, as shall be elucidated in Section 2.2, I only consider models in which at least 90% of the long-run variation in RPI is driven by two shocks, none of which is restricted upon to be the business cycle shock. (The rather conservative 90% threshold, as opposed to the ideal 100% one, is mainly motivated by the possibility of measurement error in RPI.) Section 5 presents DSGE model based Monte Carlo evidence that stresses the importance of this long-run restriction for obtaining a correct structural interpretation of the business cycle shock.

boom and subsequent early 2000s bust were generally related to overly optimistic expectations regarding information and communications technology (ICT) that were followed by a downward revision of these expectations (see, e.g., Beaudry and Portier (2004), Jaimovich and Rebelo (2009), and Karnizova (2012)). (See Appendix A in Karnizova (2012) for a list of several extracts from academic and government publications that link the boom and subsequent recession to a downward revision of overly optimistic expectations regarding ICT.)

The fact that I identify a business cycle shock directly and then ask what this shock looks like and whether it has a clear structural interpretation, as opposed to imposing identifying restrictions on an identified shock and then examining its business cycle implications, is at the core of the novelty of this paper. My fairly agnostic approach lends credence to the results and their structural interpretation because the assumptions used for identification of the business cycle shock are sound and reliable. Business cycle comovement is arguably the most salient feature of economic fluctuations; and for a shock to be considered the main force behind economic fluctuations, it must account for the majority of the business cycle variation in the real aggregates that move in tandem over the business cycle. Accordingly, the shock that drives the business cycle must produce business cycle comovement and explain most of the business cycle variation in the main macroeconomic real aggregates. I simply impose on these two attributes to characterize my identified business cycle shock, thus resulting in a credible identification procedure. That the identified business cycle shock seems to have a clear structural interpretation supports the notion that there is indeed a single economic shock that drives the bulk of economic fluctuations.

From a broader standpoint, the findings of this paper stress that the business cycle is driven by technology related fundamentals rather than noise or policy related shocks. Particularly notable is the rather strong evidence put forward by this paper that goes against the notion that noise shocks play a considerable role in driving the business cycle. The noise-driven business cycle hypothesis, which arguably is a competing hypothesis for the news-driven hypothesis, is inconsistent with this paper's findings although one cannot entirely rule out on their basis the possibility that noise shocks still play some role, albeit limited relative to IST news shocks, in driving the business cycle.

Moreover, while much of the earlier work focused on shocks to TFP or IST that affect only the fundamental to which they are related, this paper assigns an important role in driving economic fluctuations to a GPT news shock that can be interpreted as an IST news shock whose delayed materialization ultimately produces significant TFP gains. As such, the findings of this paper largely accord with and complement those of Schmitt-Grohe and Uribe (2011), who estimate an RBC model where a common stochastic trend in neutral and investment-specific productivity is found to be the main source of business cycles.[5] I find conceptually similar results to theirs, using a relatively model-free identification approach, although I also provide a news-based interpretation of my business cycle driving force.[6]

Related Literature. The general business cycle literature my paper belongs to is very large and is non-exhaustively cited above. Here I focus on describing the literature my paper is related to from a methodological standpoint. The method I use in this paper is based on the sign restrictions Structural VAR (SVAR) literature which identifies shocks of interest by employing set identification whereby sign restrictions are imposed so as to generate the set of admissible models. This literature has mainly focused on imposing restrictions on the sign of impulse responses (see, e.g., Uhlig (2005), Dedola and Neri (2007), Mountford and Uhlig (2009), Peersman and Straub (2009), and Kilian and Murphy (2012)) as well as the sign of the cross correlation function in response to shocks (Canova and De Nicolo (2002)).

More recently, Ben Zeev (2018) incorporated restrictions on the long-run forecast error variance decomposition of RPI so as to identify IST news shocks. The method in this paper incorporates both sign restrictions, i.e., requiring positive impact effects of the business cycle shock on the real aggregates, as well as restrictions on the forecast error variance of the real aggregates, so that the identified shock explains more than 50% of their two-year variation. Moreover, so as to consider models that comply with standard macroeconomic theory and thus facilitate their coming closer

[5]Using a standard Engle-Granger test (Engle and Granger (1987)) for my RPI and TFP measures, I could not reject the null of no cointegration between these two series. Importantly, however, one should keep in mind that the lack of evidence for cointegration between my RPI and TFP measures has no bearing on whether the business cycle shock can drive in tandem the long-run variation in these two variables; the reason for this is that non-cointegrated series can of course still be driven by the same shocks in the long run.

[6]Wagner (2017) estimates a similar model to that used by Schmitt-Grohe and Uribe (2011) but allows for news shocks to the common stochastic trend in TFP and IST, finding an important role for these news shocks in driving the business cycle.

to the true data generating process, I also impose that at least 90% of the long-run variation in RPI is driven by two arbitrary shocks.

The largely agnostic procedure used in this paper is conceptually similar to that employed by Uhlig (2003). Using the Maximum Forecast Error Variance (MFEV) method to identify a set of orthogonal shocks that maximally explain (in decreasing order) output variation over a five-year horizon, Uhlig (2003) found that two shocks explain more than 90% of output variation at all horizons. The rather rich array of short- and long-run restrictions I use in this paper seems to provide for a more useful framework for studying the sources of business cycles than the narrower set of restrictions used by Uhlig (2003). While my richer set of restrictions does make my approach somewhat more restrictive, I still view them as a necessary step toward correctly uncovering the business cycle shock owing to the fact that they are based on rather weak, data- and theory-consistent assumptions: The short-run restrictions are very much consistent with the salient comovement feature of business cycles and the long-run restriction accords well with basic economic theory. Notably, that my methodological approach can directly impose the restrictions that accurately characterize the nature of the business cycle shock is precisely what makes it a more suitable device for studying the question in the title of this paper.

Finally, in concurrent work that applies Uhlig (2003)'s identification approach more comprehensively by separately applying it to several macro variables and by looking at various truncation horizons, while focusing just on the first shock that moves the most of a particular variable's variation, Angeletos et al. (2018) find that the shock that drives most of economic fluctuations seems to be unrelated to long-run movements in TFP and RPI. On top of the differences already highlighted in the context of the paper by Uhlig (2003), there are two additional noteworthy differences between mine and Angeletos et al. (2018)'s empirical analysis which make a strong case for the incomparability of the results from the two analyses and for taking caution in interpreting the long-run implications of Angeletos et al. (2018)'s analysis. First, Angeletos et al. (2018) estimate a VAR in levels, which was shown by Phillips (1998) to be an unsuitable tool for properly estimating long-run impulse responses and forecast error variance decompositions both asymptotically as well as in small samples. This in contrast to stationary VARs, such as the one used in my analysis, which deliver consistent estimates of long horizon impulse responses and forecast error variance decompositions. Second, the measure of RPI used in Angeletos et al. (2018) considers the durable consumption goods sector along with the *total* investment sector, as opposed to the finer and more standard measure covering durable consumption goods and only equipment investment. Considering the entire investment sector is a too coarse measure for properly constructing a price index that corresponds to IST, which in empirical terms is normally thought to represent technology in producing firm and household equipment rather than residential or commercial structures.

Outline. The remainder of the paper is organized as follows. In the next section the details of the empirical strategy are laid out. Section 3 begins with a description of the data, after which it presents the main empirical evidence followed by a sensitivity analysis section. Section 5 provides Monte Carlo evidence from a suitable DSGE model aimed at enhancing confidence in my identification procedure's capacity to answer the question posed in the title. The final section concludes.

2 Methodology

Prior to presenting the empirical strategy in detail, I first explain the underlying framework and assumptions of the analysis employed in this paper.

2.1 Underlying Framework

While I do take a fairly agnostic identification approach in this paper, I also make an attempt to bridge the gap between my set of identified models and the true data generating process in a way that relies on rather weak, theory-consistent assumptions. Such an attempt can have value in advancing a correct structural interpretation of the business cycle shock without needing to directly impose on this shock anything other than forcing it be the shock that both produces business cycle comovement and drives the majority of business cycle fluctuations. To achieve this advancement, I focus on the long-run relation between RPI and IST, which has clear structural discipline that is implied by a variety of models.

Specifically, the general relation between RPI and IST can be illustrated by considering a two-sector model structure along the lines outlined in Justiniano et al. (2011) with separate imperfectly competitive investment and consumption sectors. Both sectors are influenced by a common TFP shock and, in addition, the investment sector is affected by an IST shock. In this set up one can derive the following equilibrium equation linking IST with RPI:

$$IST_t = \left(\frac{a_c}{a_I}\right)\left(\frac{mc_{C,t}}{mc_{I,t}}\right)\left(\frac{K_{C,t}}{L_{C,t}}\right)^{-(1-a_C)}\left(\frac{K_{I,t}}{L_{I,t}}\right)^{(1-a_I)}\left(\frac{P_{I,t}}{P_{C,t}}\right)^{-1}, \tag{1}$$

where a_j stands for the capital share in sector j ($j = C, I$); $mc_{j,t}$ is real marginal cost (or the inverse of the equilibrium markup) in sector j; $K_{j,t}/L_{j,t}$ represents the capital-labor ratio in sector j; $\frac{P_{I,t}}{P_{C,t}}$ is the relative price of investment where $P_{I,t}$ and $P_{C,t}$ represent the prices of investment and consumption goods, respectively; and IST_t corresponds to investment-specific technology. Many one sector DSGE models (e.g., Smets and Wouters (2007)) can be viewed as equivalent representations of a two-sector model that admits identical production functions across the two sectors, free sectoral factor reallocation, and perfectly competitive sectors. However, recent research (e.g., Basu et al. (2010), Justiniano et al. (2011), and Moura (2018)) has argued that the assumption of equality between RPI and IST which is based on the latter three conditions is too strong. It is clear from Equation (1) that if one of these three conditions is not met there will be a wedge between RPI and IST. Hence, I only make the weak assumption that IST is the sole source of the *long-run* variation in RPI.[7] This is the underlying identifying assumption made by papers that aimed to identify unanticipated IST shocks (see, e.g., Fisher (2006) and Canova et al. (2010)) whereby they conjectured that the only shock that has a long run effect on RPI is the unanticipated IST shock. Nevertheless, as opposed to just assuming that one shock drives IST, I allow for the possibility that part of the variation in IST is anticipated in advance.

In particular, it is assumed that IST is well-characterized as following a stochastic process

[7]For IST to be the sole source of the unit root in RPI there would need to be equal capital shares across the investment and consumption sectors, free sectoral factor reallocation in the long run, and stationarity of sectoral mark-ups. The latter is implied by macroeconomic theory as standard sectoral Phillips curves imply that mark-ups are roughly the difference between expected inflation rates and current ones (see, e.g., Justiniano et al. (2011)). Moreover, Basu et al. (2010) find that the capital share for the services and non-durables sector is 0.36 whereas that of equipment and software investment and consumer durables is 0.31. Given that the two shares are relatively close, and that it is reasonable to assume that in the long run factor inputs can freely reallocate, it seems sensible to assume that the long-run variation in RPI is driven solely by unanticipated IST shocks and IST news shocks. Notably, this assumption is quantitatively borne out by the elaborate two-sector model from Moura (2018), which uses similarly different sector-specific capital shares (0.36 and 0.30) along with sector-specific nominal frictions as well as labor and capital reallocation frictions (this model serves as the underlying true data generating process for my Monte Carlo experiments from Section 5).

driven by two shocks. The first is the traditional unanticipated IST shock, which impacts the level of technology in the same period in which agents observe it. The second is the news shock, which is differentiated from the first shock in that agents observe the news shock in advance and it portends future changes in technology. The following is an example process that incorporates both unanticipated and news shocks to IST:[8]

$$\epsilon_t = \epsilon_{t-1} + g_{t-j} + \eta_t, \tag{2}$$

$$g_t = \kappa g_{t-1} + v_t. \tag{3}$$

Here the log of IST_t, denoted by ϵ_t, follows a unit root process where the drift term itself g_{t-j} follows an AR(1) process with $j \geq 1$. j represents the anticipation lag, i.e., the delay between the announcement of news and the period in which the future technological change is expected to occur. Parameter $0 \leq \kappa < 1$ describes the persistence of the drift term. η is the conventional unanticipated technology shock. Given the timing assumption, v_t has no immediate impact on the level of IST but portends future changes in it. Hence, it can be defined as an IST news shock.

Given the above underlying theoretical framework, I only consider models that are consistent with Equations (1)-(3) in the empirical analysis below. Specifically, I impose the restriction that at least 90% of the long-run variation in RPI is driven by two shocks, none of which is restricted upon to be the business cycle shock. Ideally, one would want to require that 100% of the long-run variation in RPI is driven by two shocks but given that there could be measurement errors present in my empirical analysis and that the capital shares in the consumption and investment sectors seem to be close but not entirely identical, the 90% restriction seems a reasonable compromise.

One may argue that some restrictions on the behavior of TFP should also be incorporated in my analysis. E.g., if the identifying assumption of Barsky and Sims (2011) that two shocks drive all variation in TFP at all horizons holds (the first shock being a surprise shock that moves TFP on impact and the second being a news shock that moves it with a delay), then it is advisable to restrict the set of identified models to accord with this assumption. However, as stressed by Kurmann and Sims (2017) and Bouakez and Kemoe (2017), measured TFP likely contains mea-

[8] A similar process was used by Leeper and Walker (2011), Leeper et al. (2013), and Barsky and Sims (2011, 2012).

surement errors which in turn lead to a violation of the aforementioned identifying assumption.[9] Moreover, even if these measurement errors are transient, restricting the long-run behavior of TFP may be erroneous on the grounds that other shocks, such as GPT-type shocks, could drive some of the long-run variation in TFP. Therefore, I leave TFP behavior unrestricted in my analysis, which ex-post turns out to be a reasonable choice given that the business cycle shock drives the bulk of the long-run variation in RPI and also a considerable share of that in TFP.

2.2 Generating the Set of Admissible Models

My methodology is a set identification VAR-based method which generates a set of admissible models that comply with a defined set of restrictions, to be described below in detail. The method is a set identification one because the imposed restrictions admit a system of inequalities that in general will have either no solutions or a set of solutions. This set of solutions constitutes the set of models that satisfy my imposed restrictions. I employ Bayesian estimation and inference using a baseline empirical VAR that consists of the real aggregates, TFP, RPI, inflation, and interest rates.

Specifically, Let y_t be a kx1 vector of observables of length T and let the VAR in the observables be given as

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + B_c + u_t, \tag{4}$$

where B_is are matrices of size kxk, p denotes the number of lags, B_c is a kx1 vector of constants, and $u_t \sim i.i.d.\ N(\mathbf{0}, \Sigma)$ is the kx1 vector of reduced-form innovations where Σ is the variance-covariance matrix of reduced-form innovations. For future reference, let the stacked $(kp+1)$xk $B = [B_1, ..., B_p, B_c]'$ matrix represent the reduced form VAR coefficient matrix. Hence, the reduced form VAR parameters can be summarized by the coefficient matrix B and variance covariance matrix Σ.

[9] The focus in Kurmann and Sims (2017) is on the large revisions in the widely-used series of utilization-adjusted TFP by Fernald (2014) and these revisions' substantial effect on empirical conclusions about the macroeconomic effects of TFP news shocks identified using the Barsky and Sims (2011) method. Interestingly, and largely in accordance with the newer TFP vintages issue highlighted by Kurmann and Sims (2017), I find that older TFP vintages such as from 2011 respond to the business cycle shock to a much lesser extent. Nevertheless, since newer TFP vintages likely contain less measurement error than older ones and as such constitute better proxies for true TFP, I utilize the most recent Fernald (2014) TFP vintage in my estimations and place more trust in results based on this series than those based on older TFP vintage series.

It is assumed that there exists a linear mapping between the reduced-form innovations and economic shocks, e_t, given by

$$u_t = Ae_t. \tag{5}$$

The impact matrix A must satisfy $AA' = \Sigma$. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, C (e.g, the Cholesky factor of Σ), the entire space of permissible impact matrices can be written as CD, where D is a k x k orthonormal matrix (i.e., $D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).

Given an estimated reduced form VAR, standard SVAR methods would try to deliver point identification of at least one of the columns of A whereas set identification methods would generate the set of admissible models. In the set identification approach the aim is to draw a large number of random Bs, Σs, and Ds from their posterior distributions so as to generate a large set of models (a model here can be represented by the matrix triplet $\{B,\Sigma,D\}$) from which the set of admissible models can be obtained by checking which models comply with the imposed restrictions. I take 10^6 such posterior draws, while following the conventional Bayesian approach to estimation and inference taken by the sign restrictions literature (see, e.g., Uhlig (2005), Mountford and Uhlig (2009), Peersman and Straub (2009), and Kilian and Murphy (2012)) in assuming a normal-inverse Wishart prior distribution for the reduced-form VAR parameters and a Haar distribution for the orthonormal D matrix.[10,11] Appendix A contains a detailed description of the Bayesian estimation procedure used in this paper.

The restrictions that I impose on the set of admissible models are as follows:

1. One shock, belonging to the vector of economic shocks e_t, raises on impact the real aggre-

[10] I follow the efficient method proposed by Rubio-Ramirez et al. (2010) for generating orthonormal matrices and the associated identification, impact matrices.

[11] Notably, my identification procedure is not susceptible to the criticism posed in Arias et al. (2018) on the common use of the penalty function approach (PFA) to settings in which both zero and sign restrictions are imposed since my procedure neither applies the PFA approach nor does it impose zero restrictions. Moreover, while I acknowledge that my uninformative Haar prior for the impact D matrix does not imply nonuniform prior distributions for key objects of interest such as impulse response functions, as stressed by Baumeister and Hamilton (2015, 2018), I also highlight that the fact that my identification procedure works reasonably well when applied to artificial data from a suitable DSGE model (see Section 5) alleviates the concern that the findings from Baumeister and Hamilton (2015, 2018) have significant consequences for my analysis.

gates, i.e., output, hours, consumption, and investment, and explains at least 50% of the two-year variation of the real aggregates.

2. At least 90% of the long-run variation in RPI is driven by two arbitrary shocks belonging to e_t.

Imposing set of restrictions 1 constitutes a necessary step for directly examining the nature of the driving force of business cycle fluctuations. The latter set of restrictions ensures that the estimated set of admissible models only contains models in which one shock explains the majority of business cycle fluctuations. Note that I also require that this shock is capable of generating business cycle comovement by restricting the real aggregates to rise at the impact horizon in response to the business cycle shock. This is an important restriction given the stylized fact that the real aggregates move in tandem over the business cycle. Hence, the shock that I am trying to capture both generates business cycle comovement and explains the majority of business cycle fluctuations. Notably, however, this initial step in and of itself is not sufficient for providing an answer to the sought after question of this paper as it would also be necessary to examine the common characteristics of the business cycle shock so as to determine if there is truly a single common economic shock that drives the majority of business cycles.

Restriction 2 ensures that I am only considering models that are consistent with Equations (1)-(3) so as to impose some structural discipline on the estimated models in terms of being consistent with standard macroeconomic theory. This in turn facilitates bringing the identified models closer to the true data generating process, which can have much value in advancing a correct structural interpretation of the business cycle shock. Note that Restriction 2 is independent of set of restrictions 1 in that the two shocks driving the long-run variation in RPI can be any pair of shocks belonging to e_t. I.e., I do not restrict upon the business cycle shock to be one of the shocks contained in this pair, effectively letting the data determine if the business cycle shock belongs to this pair. Section 5 presents DSGE model based Monte Carlo evidence that stresses the importance of this long-run restriction for obtaining a correct structural interpretation of the business cycle shock.

I search over all drawn models and collect only those models that comply with Restrictions 1 and 2 whereas models that do not comply with these restrictions are discarded. Once all of the models are collected, it is possible to analyze them and try to structurally characterize the business cycle shock.

3 Empirical Evidence

In this section the main results of the paper are presented. I first provide a brief description of the data used in my analysis, followed by the main empirical results from my baseline VAR.

3.1 Data

The baseline VAR includes eight variables: TFP, RPI, output, hours, consumption, investment, inflation, and interest rates. For the TFP series, I employ the quarterly series on total factor productivity (TFP) for the U.S. business sector, adjusted for variations in factor utilization (labor effort and capital's workweek), constructed by Fernald (2014).[12]

RPI is measured in the standard way as a quality-adjusted investment deflator (see, e.g., Greenwood et al. (1997, 2000), Fisher (2006), Canova et al. (2010), Beaudry and Lucke (2010), and Liu et al. (2011)) divided by a consumption deflator. The quality-adjusted investment deflator corresponds to equipment and software investment and durable consumption and is based on the Gordon (1990) price series for producer durable equipment (henceforth the GCV deflator), as later updated by Cummins and Violante (2002), so as to better account for quality changes. More recently, Liu et al. (2011) used an updated GCV series constructed by Patrick Higgins at the Atlanta Fed that spans the period 1959:Q1:2017:Q3. I use this updated series as my measure for the quality-adjusted investment deflator.[13] The consumption deflator corresponds to nondurable and service consumption, derived in chain-weighted form from the National Income and Product Accounts (NIPA).

The nominal series for output, consumption, and investment are taken from the Bureau of Economic Analysis (BEA). Output is measured as GDP, consumption as the sum of non-durables

[12] http://www.frbsf.org/economics/economists/staff.php?jfernald.

[13] I thank Patrick Higgins at the Atlanta Fed for providing me with this series. The reader is referred to the appendix in Liu et al. (2011) for a description of the methods used to construct the series.

and services consumption, and investment is the sum of personal consumption expenditures on durables and gross private domestic investment. The nominal series are converted to per capita terms by dividing them by the civilian non-institutionalized population aged sixteen and over. I use the corresponding chain-weighted deflators to obtain the real series. The hours series is log of per capita total hours worked in the non-farm business sector. Inflation is measured as the percentage change in the CPI for all urban consumers and the nominal interest rate is the three month Treasury Bill rate.[14] The data series span the period 1959:Q1-2017:Q3.

3.2 Baseline Results

I first present the impulse responses and forecast error variance (FEV) decomposition results with respect to the business cycle shock after which results pertaining to the shock realizations are presented. Both sets of results enable me to derive a structural interpretation of the shock.

Impulse Responses and Variance Decompositions. My empirical VAR includes eight variables: TFP, RPI, output, investment, consumption, hours worked, inflation, and interest rates. Apart from hours, inflation, and interest rates, which are assumed to be stationary and enter the system in levels, all other variables enter the system in first differences.[15] The system is estimated as a stationary VAR as opposed to a VAR in levels due to the superiority of the former over the latter in terms of the identification of the long-run impulse responses (Phillips (1998)).[16] The Akaike information criterion favors four lags whereas the Schwartz and Hannan-Quinn information criteria favor two and one lags, respectively. As a benchmark, I choose to estimate a VAR with three lags. The results are robust to using a different number of lags.

The set of admissible models consists of 1297 models (out of a total of 10^6 posterior draws

[14]To convert monthly population, inflation, and interest rate series to quarterly series, I take the average over monthly observations from each quarter.

[15]Importantly, Restrictions 1 and 2 are imposed on the cumulative impulse responses of the relevant first-differenced variables so that variables' responses at a particular horizon correspond to the difference between their *levels* in that horizon and their pre-shock level (relative to cumulative trend growth up to that horizon).

[16]Applying the cointegration test developed in Pesaran et al. (2001) to my model, which is a mixture of both non-stationary and stationary variables and thus requires using the cointegration test from Pesaran et al. (2001), I found no evidence for cointeration among the non-stationary variables in my model. Therefore, I resorted to estimations that abstract from cointegration.

of models). Figures 1a and 1b depict the median and 84th and 16th percentiles of the posterior distributions of impulse responses and FEV contributions at all horizons up to the 10 year one, respectively.

By construction, the identified shock raises the real aggregates (output, hours, investment, and consumption) on impact and drives the bulk of their business cycle variation. The 16th percentile impact effects of IST news shocks on output, hours, investment, and consumption are 0.32%, 0.19%, 1.1%, and 0.2%, respectively, while the median impact effects are 0.41%, 0.26%, 1.4%, and 0.26%, respectively. All of the latter effects are economically significant and point to the strong business cycle comovement that the business cycle shock generates. It should be noted that these significant effects are not imposed upon by construction as the only restriction imposed on the impact effects is that they are positive. The 16th percentile contributions of IST news shocks to the variation in output, hours, investment, and consumption at the two-year horizon are 59%, 55%, 55%, and 53%, respectively, while the median contributions are 68%, 66%, 63%, and 61%, respectively, all indicating that the identified shocks are the major force behind the business cycle. While the latter contributions were restricted to be at least 50%, it is apparent that a large part of the distribution of contributions clearly contains bigger values. In terms of the implications of the business cycle shock for inflation and interest rates, the results indicate that the shock is deflationary and raises interest rates.

So as to obtain information on the structural features of the shock, I now turn to focusing on its long-run implications for RPI and TFP. Table 1 shows the median and 84th and 16th percentiles of the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock. The median contributions to the long-run variation in RPI and TFP are 80% and 54%, respectively, with corresponding long-run impulse responses of -2.4% and 1%. These estimates clearly indicate that the business cycle shock has very large effects on both variables, where that on RPI strongly suggests that this shock is likely to be an IST shock. In the presence of the standard assumption that IST shocks are the sole source of the long-run variation in RPI, this 80% FEV contribution estimate implies that the business cycle shock is very unlikely to contain a non-IST shock.

More formally, note that any identified shock is a linear combination of reduced form innovations, each of which is itself a linear combination of structural shocks (under the standard assumption of equality between the number of observables and number of structural shocks); this, in turn, renders the identified business cycle shock representable as a linear combination of shocks that include both IST and non-IST shocks. Hence, the fact that it explains 80% of the long-run variation in RPI implies that the weight on the non-IST shock portion of this linear combination is $1 - 0.8^{0.5}$, or 9%.[17,18] This emphasizes the importance of the RPI FEV results in facilitating the structural interpretation of the business cycle shock as an IST shock. And, importantly, it rules out the interpretation of the business cycle shock as a TFP shock.

How, then, can one interpret the strong long-run effect of the business cycle shock on TFP? Notably, the effect on TFP only becomes really noticeable at medium- to long-run horizons. E.g., we see from Figure 1b that only 10% of TFP variation is accounted for by the business cycle shock at the five-year horizon. This TFP behavior is consistent with a GPT-based interpretation of IST where gains in the latter lead to medium- and long-run gains in TFP by inducing long-term fundamental changes in the production process of the sectors using the new IST-related goods.[19] Taken together, the results on the long-run behavior of RPI and TFP indicate that the business cycle shock is either an unanticipated IST shock or an IST news shock, as macroeconomic theory implies that IST is the long run driver of RPI, and that owing to their general-purpose nature IST improvements lead to long-term gains in TFP. I now turn to demonstrating how additional information on the shock series itself can help distinguish between the two IST shocks and provide an interpretation of the shock as an IST news shock.

[17] To see this, denote the identified business cycle shock by ϵ_t^{bs} and let it be represented as a weighted average of IST and non-IST shock components, $\epsilon_t^{bs} = \omega_1 \epsilon_t^{ist} + \omega_2 \epsilon_t^{non\_ist}$. (The ϵ_t^{ist} component can be taken to be the sum of surprise and anticipated IST shocks, while $\epsilon_t^{non\_ist}$ can be taken to be the sum of all remaining non-IST shocks.) Since in the long run only the first component should have a non-negligible contribution to RPI variation and since the long-run RPI FEV attributable to the business cycle shock is 0.8, we can deduce that $\omega_1^2 = 0.8$. But since $\omega_1 + \omega_2 = 1$, we obtain that $\omega_2 = 1 - 0.8^{0.5} = 0.09$.

[18] Note that the long-run estimates are not directly shown in Figures 1a and 1b as these figures pertain to only the first 10 years following the shock whereas the long-run estimates are computed from the permanent responses of the non-stationary variables. Given the rather strongly gradual nature of the impulse response of RPI and TFP, the 10 year estimates are downward biased estimates of the long-run response estimates.

[19] These results are consistent with those from Chen and Wemy (2015), who find that IST changes are an important source of long-run TFP movements.

Boom-bust Behavior of the Shock in the Late 1990s-Early 2000s Period. The real economy and stock market experienced a significant boom in the late 1990s which was followed by a bust in the early 2000s. In particular, in the period 1997-1999 Shiller's cyclically adjusted price-earnings ratio, computed as the ratio of the real price of the S&P 500 index to average real earnings over the previous 10 years, reached its highest levels in the sample peaking at the end of 1999 from which point it began its bust period bottoming out in February 2003. The common view by economists is that the boom and subsequent bust were generally related to overly optimistic expectations about IST that were followed by a downward revision of these expectations (see, e.g., Beaudry and Portier (2004), Jaimovich and Rebelo (2009), Karnizova (2012) (see also references therein), and Ben Zeev (2018)).

The first two rows of Table 2 present the median and 84th and 16th percentiles of the average value of the 1997:Q1-1999:Q4 and 2000:Q1-2003:Q1 shock sub-series for both the business cycle shock and the other shock driving the long-run variation in RPI, respectively.[20] It is apparent that a clear boom-bust pattern is prevalent in the business cycle shock series where the average shock realization is significantly positive in the boom period while being significantly negative during the bust period. The median mean realization for the business cycle shock in the boom period is 0.49 standard deviations compared to 0.04 standard deviations for the corresponding counterpart of the other long-run RPI shock. The median mean realization of the bust period is -0.38 for the business cycle shock compared to -0.06 for the other long-run RPI shock. And the posterior bands around these median estimates clearly indicate that one can be fairly confident in inferring that the business cycle shock strongly exhibits a boom-bust type behavior in the late 1990s and early 2000s period, whereas the other long-run RPI shocks exhibits no such clear pattern.

While the above-reported results demonstrate that the business cycle shock exhibits an ap-

[20] In 1233 models out of the set of 1297 admissible models the business cycle shock is also one the two IST shocks, i.e., the shocks driving long-run RPI variation. Moreover, out of these 1233 models, the other long-run RPI shock explains at least 5% of the long-run variation in RPI in 982 models. Hence, the results on the other long-run RPI shock are based on these 982 models so as to only consider models where the business cycle shock and other long-run RPI shock are both IST shocks and where the other long-run RPI shock is a true IST shock rather than possible measurement error. Notably, I also show the results on the other long-run shock as it is important to check that the other shock that explains the long-run variation in RPI does not display this boom-bust pattern given that this would undermine my ability to obtain a structural interpretation of the business cycle shock based on the boom-bust feature.

parent boom-bust behavior in the late 1990s and early 2000s period, it seems worthwhile to also compute the historical decomposition of this boom-bust period in terms of the contribution of the two shocks to movement in investment over this period given that this period is considered to have been an investment-driven episode. The first two rows of Table 3 present the median and 84th and 16th percentiles of the relative contribution of the business cycle shock and the other long-run shock to the movement in investment in the boom-bust period, respectively. In particular, the results from Table 3 show, in percentage terms, how much of the movement in investment in the boom and bust periods is accounted for by the two shocks.[21] It is clear from Table 3 that the business cycle shock accounts for a very significant share of both the investment boom in the late 1990s as well as the subsequent investment bust in the early 2000s.[22] The median shares in the boom and bust periods explained by the business cycle shock are 97% and 161%, respectively, while those explained by the other long-run RPI shock are very negligible and statistically insignificant. The 16th percentile shares explained by the business cycle shock for the boom and bust periods are also large, amounting to 62% and 94%, respectively. These are very strong results which indicate that the business cycle shock is the main force behind the boom-bust investment episode of 1997-2003, whereas the other long-run RPI shock is a negligible one.

Taken together, the results presented so far indicate that the business cycle shock can be interpreted as an IST news shock whose general-purpose properties lead to long-term gains in TFP. I now turn to showing that this shock has also played an important role in driving the actual recessions that have taken place in my sample period.

Historical Decomposition. My use of the FEV restriction in defining the business cycle shock in this paper is based on the notion that such a shock should have a major contribution to economic fluctuations *on average*. But one additional property such a shock should desirably posses is having

[21]The relative contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ investment\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for investment is assumed to be 2.8%, which is the average growth rate in the sample period. Note that a relative contribution of one implies that all of the gain or loss in investment is accounted for by the shock. Investment increased relative to its steady state growth by 17% in the boom period while it declined by 11% in the bust period relative to its potential growth rate.

[22]In the next section, I apply my method to a VAR that includes stock prices from which it is confirmed that the business cycle shock also drove a big share of the movement in stock prices during the boom-bust period.

an important role in driving *actual*, historical economic downturns. To test whether my business cycle shock posses this property, I have computed the historical contribution of this shock to the eight NBER-determined U.S. recessions since 1959.

Table 4 shows the results from doing this historical decomposition. In particular, for each recession the median contribution of the business cycle shock to the peak-to-trough percentage change in each of the four real aggregates' per capita levels (in deviation from trend growth) is estimated. Trend growth rates are computed from the average growth rates of corresponding per capita real aggregates over the sample. The results indicate that the business cycle shock was an important driving force behind seven of the last eight U.S recessions. The only recession in which the business cycle shock played a limited role was the 1981-1982 recession, which is commonly thought of as having been driven by aggressively contractionary monetary policy. Apart for this recession, the business cycle shock contributed to all recessions in an economically and statistically significant manner.

The most recent recession (2007-2009), in which output loss was 7.9%, seems to have been driven in large part by the business cycle shock which contributed 5.5% to that accumulated decline.[23] The business cycle shock has also contributed 2.6%, 3.9%, and 1.5% to the accumulated 2.6%, 5.6%, and 2.6% output losses during the 1960-1961, 1973-1975, and 1990-1991 recessions, respectively. Moreover, that 1.2% of the 1.7% output loss in the 2001 recession is attributed to the business cycle shock is consistent with the IST-news-based interpretation of this shock advanced in this paper, which draws on the notion that a downward revision of expectations about future IST took place after the IST news driven boom of the late 1990s.

Overall, the historical decomposition results emphasize that the business cycle shock is not only a dominant driver of U.S. business cycles *on average*, but also a dominant driver of actual historical recessions that have taken place in my sample period. I now turn to show that the stationary hours specification is superior to a non-stationary hours one, where the latter is demonstrated to be an erroneous modeling choice that likely leads to misguided inference.

[23] Importantly, the results of this paper are not driven by the inclusion of the recent recession in the sample as I have confirmed that stopping the sample at 2007:Q4 yields similar results to the baseline ones. These results are presented in the first robustness check of Section 4.4.

Hours Stationarity and the Low-Frequency Comovement between Hours and RPI and TFP. The results presented above were obtained from a VAR in which hours worked were assumed to be stationary and thus entered the system in levels. However, entering hours in differences in the VAR results in a negligible contribution of the business cycle shock to the variation in both RPI and TFP. (The impulse responses and FEV contribution results for the differenced hours specification appear in Figures 2a and 2b, respectively.) The contributions of the shock to the long-run variation in RPI and TFP, not directly shown in Figure 2b, are 5% and 2%, respectively. While the differenced hours specification results in a permanent effect of the business cycle shock on hours (again, not directly shown in Figure 2a, but is clearly indicated by the leveling-off of the response at medium-run horizons), which is at odds with standard macroeconomic theory and thus limits the credibility of this specification as a suitable way for modeling hours, the results from the differenced hours specification are still a concern whose source is worth exploring and understanding.

The issue of how hours worked should enter VARs with long-run restrictions has been found to be particularly relevant to estimating the effect of technology shocks on hours, with researchers entering hours in first-differences generally finding a drop in hours (see Shea (1998) and Gali (1999)) while those entering hours in levels finding a rise in hours (see Christiano et al. (2003, 2007)). More recently, Gospodinov et al. (2011) found that the contrasting conclusions from levels and differenced hours specifications can be explained by a small low-frequency comovement between hours worked and productivity growth, which is allowed for in the levels specification but is implicitly shut down in the differenced specification.

The findings by Gospodinov et al. (2011) go a long way toward laying down the basis for comprehending the stark differences between the first-differences and levels hours specifications in terms of the contribution of the business cycle shock to RPI and TFP long-run variation. Gospodinov et al. (2011) highlighted that even a small low-frequency correlation between hours and productivity growth can account for the difference in results on technology shocks between levels and first-differenced specifications; I shall now demonstrate that the low-frequency correlation of hours with the growth rates of RPI and TFP is very large, making it all the more important to enter hours in the VAR in levels so as to allow for this low-frequency correlation rather than to erroneously shut it down via the differenced hours specification.

Table 5 shows the correlations between the HP trends of log and log-first-differences of hours worked and HP trends of log-first-differences of RPI and TFP. While the low-frequency correlations of hours in levels with RPI and TFP growth rates are very high (0.74 and 0.52, respectively), they are negligible and even negative when hours are considered in log-first-differences. This stresses the importance of entering hours in levels so as to allow for its strong low-frequency comovement with RPI and TFP growth rates, as opposed to wrongly eliminating it via a first-difference specification. Since Gospodinov et al. (2011) have reported significant biases from a first-differenced specification in the presence of even a small low-frequency component, it is likely that the strong correlations reported in Table 5 would lead to significant biases for my setting if I were to estimate a VAR with log-first-differenced hours.

To formalize this argument, I now present evidence from two Monte Carlo experiments. In the first one, I generate 100 artificial data sets from VARs that are identical to my empirical VAR, i.e., with hours worked in levels and which comply with Restrictions 1 and 2, and apply my identification procedure (based on 10^5 posterior draws) to each artificial data set using a VAR that includes hours in first-differences. The second experiment is identical to the first only that I apply my identification procedure to each artificial data set using a VAR that includes hours in levels, rather than first-differences. The objective of the first experiment is to study the long-run estimation bias from erroneously entering hours in first-differences in the VAR, while that of the second experiment is to examine the identification precision from correctly specifying hours in levels.[24]

To mimic as much as possible the low-frequency aspects of the actual data used in my empiri-

[24] I refrain from focusing on Monte Carlo experiments based on data generating processes (DGPs) where hours are differenced as these were found to encompass the following data-inconsistent features: on average, they produce small low-frequency correlations between hours worked and the growth rates of RPI, TFP, output, and consumption (and significantly negative, rather than positive, correlation with investment growth), which is in stark contrast to the actual low-frequency correlations observed in actual data and the correspondingly consistent average correlations produced by stationary hours DGPs; applying differenced hours VAR estimation to artificial data generated from differenced hours DGPs that do comply with the low-frequency nature of the data mostly results in null set identification, making it unlikely that a differenced hours DGP could have produced the non-empty set of admissible models obtained from applying the differenced specification to actual data; and hours exhibit a significant long-run response to the business cycle shock, which is strongly at odds with economic theory. Taken together, these facts indicate that differenced hours based DGPs are very unlikely to have generated the actual data that we observe in reality.

cal analysis, I only consider artificial data sets for which the following low-frequency correlations hold (with resect to variables' HP trends): *i*) RPI growth rate is negatively correlated with TFP, output, investment, and consumption growth rates as well as hours in levels; *ii*) TFP growth rate is positively correlated with output, investment, and consumption growth rates as well as hours in levels; *iii*) RPI (TFP) growth rate is positively (negatively) correlated with hours in first-differences; and *iv*) RPI growth rate is more correlated with hours in levels in absolute terms than the corresponding correlation between TFP growth rate and hours in levels. Importantly, the estimation bias is similar when these low-frequency correlations are not restricted to hold for the artificial data sets. That said, ensuring that these low-frequency features hold is important for making the Monte Carlo experiment more realistic in terms of being based on artificial data that share common low-frequency features with the actual, empirical data.[25]

Figures 3a and 3b show the mean estimated median and 84th and 16th percentile impulse responses and FEV contributions to the variables' variation of the identified business cycle shock over a ten year horizon, along with the corresponding mean true responses and contributions from the true model. The mean *estimated* impulse responses and FEV contributions are averages over monte carlo simulations; the mean *true* impulse responses and FEV contributions are averages over the 100 data generating processes. It is apparent that the mean estimated median responses and FEV contributions for RPI and TFP are significantly downward biased. E.g., while the true FEV contribution to RPI 10-year variation is 57%, the average estimated median contribution is 23%. The numbers for the long-run horizon (not directly shown in the figures) are similarly far apart at 80% and 38%. Similar discrepancies hold for TFP also.

Notably, the proportion of Monte Carlo simulations where estimated median long-run contributions to RPI and TFP FEVs are both below 0.1 is 36% (i.e., for 36 out of the 100 considered artificial data sets, my identification produces an estimated median long-run RPI and TFP FEV contribution of less than 0.1); the proportion for the contributions being both below 0.05 is 24%. These significant proportions indicate that it is very much possible that applying an erroneous

[25] I only restrict the sign of these low-frequency correlation, rather than resorting to more restrictive bounds, so as to refrain from overly restraining the DGP. Notably, Restriction *iii* ensures that the low-frequency correlation of hours with RPI and TFP growth rates is eliminated once hours are considered in first-differences.

differenced hours VAR specification to the actual data could result in the negligible long-run FEV shares I find when specifying hours in first-differences, supporting the view that the actual data is likely generated by a stationary hours based data generating process. In sum, these proportions stress the strong likelihood of erroneously inferring that the business cycle shock is unrelated to long-run movements in RPI and TFP when using a VAR with differenced hours.

Figures 4a and 4b correspond to Figures 3a and 3b with the only difference being that they are based on correctly specifying hours in levels in the estimated VARs. Clearly, the mean estimated median responses and FEV contributions for RPI and TFP are now very close to the corresponding mean true counterparts, which is in stark contrast to the results from Figures 3a and 3b. Taken together, the Monte Carlo results presented here emphasize that correctly specifying hours in levels is crucial to structurally interpreting the business cycle shock in an appropriate manner.

Lifting the Long-Run Restriction. From a technical standpoint, Restriction 2 is independent of set of restrictions 1 and is accordingly not needed for the identification of the business cycle shock. However, the structural discipline this restriction puts on the long-run behavior of RPI is valuable for the structural interpretation of the business cycle shock as it uses rather weak assumption to make the set of admissible models be more theory-consistent and hence facilitates their coming closer to the true data generating process. (DSGE model based Monte Carlo evidence supporting this argument is shown in Section 5.) Notwithstanding the merit of including Restriction 2 in the analysis, one may argue that showing that the structural interpretation of the business cycle shock advanced in this paper holds also in the absence of this restriction can serve to increase this interpretation's validity.

Toward this end, I now present results from estimating the baseline VAR using only set of restrictions 1. I.e., I now impose no structural discipline on the long-run behavior of RPI. The impulse responses and FEV contributions are shown in Figures 5a and 5b, respectively, while the first two rows of Table 6 depict the long-run impulse response and FEV contributions of the business cycle shock for RPI and TFP and the first two rows of Table 7 present its mean realizations for the boom-bust period and contribution to the variation in investment over this period. The results are based on 10^6 randomly generated models from which a total of 17176 admissible models were collected.

It is clear that the business cycle shock still has a significant and rather large effect on both RPI and TFP, explaining 44% and 38% of their long-run variation, respectively. While these numbers are lower than their baseline counterparts, they are still sufficiently large on their own to make a valid case that there is likely to be an important IST shock component in the business cycle shock. Turning to the boom-bust based results from Table 7, it becomes apparent that the business cycle shock continues to exhibit a very clear boom-bust pattern over the late 1990s-early 2000s period in tandem with explaining most of the variation in investment over this period. Taken together with the long-run based results, and drawing again on the IST-news-based narrative of this period, these findings indicate that the business cycle shock is likely to be an IST news shock.[26]

I end this section with a discussion on why it is misguided to interpret the business cycle shock as a combination of TFP and IST news shocks instead of a pure IST news shock. Given that the business cycle shock does not explain the long-run variation in RPI as much as it does in the baseline case, one may argue that there is now more room to argue for a TFP news component being present in this shock. However, there are two reasons that cast serious doubt on the validity of this argument. First, the DSGE model based Monte Carlo evidence presented below in Section 5.2 stresses that one need not interpret these quantitative FEV differences as evidence for a lack of robustness; rather, they emphasize the importance of imposing the RPI long-run restriction for properly interpreting the results from a structural standpoint. Second, the clear boom-bust pattern exhibited by the business cycle shock renders the TFP news shock view likely misguided. To more forcefully argue this, I have computed the mean realizations for the late 1990s-early 2000s boom-bust period for the TFP news shock series from Barsky and Sims (2011), which are 0.22 and 0.09 (in standard deviation units) for the boom and bust periods, respectively. I.e., the arguably pure TFP news shock identified in the literature does not exhibit a boom-bust pattern over the late 1990s-early 2000s period, thus supporting the IST-news-based interpretation advanced in this

[26] An additional important point worth highlighting is that the fact that inflation falls in tandem with the rise in economic activity makes it unlikely that the business cycle shock is a pure demand shock, or at least a shock whose main propagation mechanism is demand driven. This observation allows to argue that it is unlikely that the business cycle shock corresponds to demand-type shocks such as monetary policy shocks, government spending shocks, noise shocks, credit supply shocks, and uncertainty shocks.

paper.[27]

4 Robustness Checks

This section examines the robustness of the baseline results along seven main dimensions. The first speaks to the possibility that there may not exist a perfect linear mapping between VAR innovations and economic shocks. The second is that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The third relates to the inclusion of stock prices in the VAR. The fourth concerns the potential implications of the financial crisis and zero lower bound (ZLB) periods for my results. The fifth pertains to the stationary specification choice used in my baseline VAR. And the sixth and seventh concern the robustness of the results to using Fernald (2014)'s investment TFP measure and a PCE-based inflation measure, respectively.

4.1 Addressing Potential Invertibility Issues

As emphasized in Fernandez-Villaverde et al. (2007), for there to be a linear mapping between VAR innovations to economic shocks, as it is assumed in Mapping (5), the observables ought to be capable of perfectly forecasting any unobserved state variables present in the true model. If this is the case, the moving average (MA) process of the true model is said to be invertible, or fundamental.

Given that non-invertibility is fundamentally a product of informational deficiency, one practical approach to testing whether non-invertibility is affecting one's results is by checking whether the VAR contains sufficient information such that the true MA process is invertible. Following this reasoning, Forni and Gambetti (2014) have developed a formal statistical test of the null hypothesis of invertibility that is based on checking for orthogonality of the identified shock at hand with respect to the past values of the principal components of a large macroeconomic data set. Forni

[27] I have also confirmed that these shock realization averages for TFP news are not artifacts of the fact that a relatively old TFP vintage was used in Barsky and Sims (2011). E.g., when identifying TFP news shocks from a VAR that is similar to that used in Barsky and Sims (2011) but that includes the most recent TFP vintage from Fernald (2014), the resulting mean realization for the bust period is even more positive.

and Gambetti (2014) have shown that the null of invertibility is rejected if and only if orthogonality is rejected, in which case the identified shock cannot be considered a structural shock.

To conduct the invertibility test for my identified IST news shock, I extract the principal components from the large quarterly FRED-QD database consisting of 254 quarterly macroeconomic and financial series, all of which have been transformed to induce stationarity.[28] The series span the period 1959:Q1-2015:Q3. Consistent with the invertibility test proposed and used in Forni and Gambetti (2014) and Forni et al. (2014), Table 8 reports the p-values of the F-test of the regression of the median business cycle shock series on three lags of the first n principal components, where n goes from 1 to 8. I truncate n at 8 as the first eight principal components explain 53% of the total variance of the FRED-QD data set. In all specifications the null of invertibility cannot be rejected at the 5% level, indicating that the identified business cycle shock passes the invertibility test.

Moreover, Table 8 also reports the R^2s associated with each regression in line with the important message from Beaudry et al. (2015) that one must look at the explanatory power of lagged principal components in addition to the standard F-test p-values so as to ascertain the quantitative importance of any potential non-invertibility. Beaudry et al. (2015) show that non-invertibility is likely to be quantitatively unimportant in terms of its effect on identification precision even for R^2s in the order of 0.2. Hence, that the R^2s of my regressions never exceed 0.14 is encouraging and enhances confidence that the results of this paper are not driven by potential non-invertibility.

4.2 Results for Post-1982 Sub-Sample

One may be concerned that the VAR coefficients might not be stable over the entire sample period. Moreover, the VAR innovations may not be homoscedastic. Hence, I now present results from applying my methodology to a post-1982 sub-sample where it is demonstrated that these sub-sample results, which are much less likely to suffer from potential coefficient instability or heteroscedasticity (see, e.g., Stock and Watson (2007)), are essentially the same as the large sample results.

Figures 6a and 6b show the impulse responses and FEV contributions from this exercise; and

[28] The data was downloaded from Michael McCracken's webpage at https://research.stlouisfed.org/econ/mccracken/fred-databases/.

the third and fourth rows of Tables 1, 2, and 3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. The figures are based on 10^6 randomly generated models from which a total of 2436 admissible models were collected. It is apparent the main results are unchanged for the post-1982 sub-sample period: the business cycle shock accounts for 81% and 54% of the long-run variation in RPI and TFP, respectively, significantly reducing the former while raising the latter, and exhibits a strong boom-bust behavior in the late 1990s and early 2000s period being a major driver of investment variation over this period.

4.3 Adding Stock Prices to the VAR

Given this paper's IST-news-based interpretation of the business cycle shock and given that it is fairly reasonable to assume that stock prices contain information about future IST progress, a natural extension of the benchmark analysis would be to add stock prices to the baseline VAR. If the business cycle shock were truly an IST news shock, then we should expect to see a significant response of stock prices to this shock on impact. Moreover, since the late 1990s and early 2000s period was characterized by a boom-bust pattern in stock markets, adding stock price to the baseline VAR would allow to examine the contribution of the business cycle shock to this boom-bust pattern and further establish the IST-news-based interpretation of the business cycle shock.

Toward this end, I add to the baseline VAR the log-first-difference of the real S&P 500 Index, obtained from Robert Shiller's website. This series is converted to quarterly frequency by averaging over the monthly observations from each quarter. Figures 7a and 7b show the impulse responses and FEV contributions from this exercise; and the fifth and sixth rows of Tables 1, 2, and 3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Moreover, Table 9 shows the contribution of the business cycle shock to stock prices variation over the boom-bust period. Results are based on 10^6 randomly generated models from which a total of 338 admissible models were collected.

It is apparent that all of the baseline results are robust to the inclusion of stock prices in the VAR. Interestingly, the business cycle shock generates a significant impact jump in stock prices and is also an important driver of their business cycle variation, confirming the view that stock prices contain valuable information about the future value of IST. Specifically, the median contribution of the business cycle shock to the two-year variation in stock prices is 41% and the median impact effect of the shock on stock prices is highly significant at 3.2%. Moreover, as Table 9 confirms, the business cycle shock played a major role in driving stock prices during the boom-bust period with median contributions of 62% of the late 1990's boom in stock prices and 30% of the decline in the bust period.[29] Overall, the results support the interpretation of the business cycle shock as representing an IST news shock.

4.4 Financial Crisis and ZLB Periods

The inclusion of the financial crisis period (2008-2009) and associated ZLB period (2009-2014) in my baseline sample could potentially affect this paper's results through three main channels. The first is that the Great Recession period was a very unique episode in terms of the large credit supply shocks it saw; one may also want to consider results that are based on more normal, non-crisis periods. The second is that the ZLB period constitutes a structural change in the U.S. economy and therefore may bias my estimation. And the third is that my interest rate variable, the 3-months T-Bill rate, remains roughly constant during the ZLB period which in turn may also potentially bias my results. To address these three concerns, I proceed in three steps. First, I show results from a sample that excludes the financial crisis and ZLB periods, i.e., 1959-2007. Second, I use the WU and XIA (2016) shadow rate series instead of the three month T-Bill rate while running estimation over the same sample as I do in my baseline estimation. Lastly, instead of using a short-term government bond yield which was constrained by zero during the ZLB period, I use the 10-year Treasury rate which was unconstrained during this period. The first exercise addresses the concern related to the first two aforementioned channels; and the next two address the concern pertaining to the third channel. I now turn to presenting the results from these three estimation

[29] Relative to steady state growth as computed from the sample's average growth rate of stock prices, the stock market grew by 52% in the period 1997-1999 and lost 53% of its value in the subsequent bust period.

exercises.

Results from a 1959-2007 Sample. Figures 8a and 8b show the impulse responses and FEV contributions from the 1959-2007 sample based estimation; and the seventh and eighth rows of Tables 1, 2, and 3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 365 admissible models were collected.

It is apparent that the IST-news-based interpretation of the business cycle shock is also borne out by the results of this specification, with the business cycle shock continuing to account for most of the long-run variation in RPI and the significant boom-bust nature of this shock in the late 1990s-early 2000s period remaining in tact. These results are especially encouraging in confirming that my baseline results are insensitive to the exclusion of the Great Recession period and the apparent important role of the business cycle shock in driving it, as indicated by the historical decomposition results from Table 4. Also worthwhile noting is the fact that the exclusion of the financial crisis and ZLB periods has no bearing on the significant rise in interest rates observed for the baseline case.

Results from Using the WU and XIA (2016) Shadow Rate Series. The results from replacing the baseline three month T-Bill rate with the shadow rate from WU and XIA (2016) appear in Figures 9a and 9b and the ninth and tenth rows of Tables 1, 2, and 3. The sample used for this estimation, as dictated by the sample coverage of the shadow rate series, is 1960:Q1-2015:Q4 where quarterly values are averages of raw monthly values of this series. Results are based on 10^6 randomly generated models from which a total of 915 admissible models were collected.

Notably, this replacement has little effect on the baseline results and the associated IST-news-based interpretation of the business cycle shock. Moreover, the shadow rate, which serves as a better proxy for the stance of monetary policy in a ZLB environment than standard short-term interest rates, rises significantly in response to the business cycle shock in largely similar fashion to the baseline case. This rise is also somewhat stronger than that from the baseline specification, which is to be expected given that the shadow rate fluctuates in the ZLB period as opposed to the three month T-Bill rate.

Results from Using the 10-year Treasury Rate. The results from replacing the baseline three month T-Bill rate with the 10-year Treasury Rate are shown in Figures 10a and 10b and the eighth and seventh to last rows of Tables 1, 2, and 3. Results are based on 10^6 randomly generated models from which a total of 1027 admissible models were collected.

Here too one can think of the long-term, 10-year Treasury rate as a better measure of the true stance of monetary policy in a ZLB environment than common short-term interest rates but in more general terms it effectively captures markets perceptions of the future stance of monetary policy. As such, its insignificant rise observed from Figure 10a serves as evidence that the contractionary nature of monetary policy in response to the business cycle shock is insufficiently persistent to generate a significant rise in long-term interest rates. Nevertheless, the clear robustness of the results regarding the long-run implications and late 1990s-early 2000s boom-bust behavior of this shock informs us that the validity of the IST-news-based interpretation of the business cycle shock maintains also for this specification.

4.5 Alternatives to the Stationary VAR Specification

My opting to specify a stationary VAR where TFP, RPI, output, consumption, and investment are log-first-differenced in the VAR can be warranted on the basis of both the evidence that *i*) statistical cointegration tests could not reject the null of no cointegration among the non-stationary variables in my VAR (see Footnote 16) and that *ii*) hours should be treated as a stationary variable that should accordingly be kept in levels in the VAR (see discussion beginning on Page 18), as well as the importance of being able to have meaningful inference about the long-run implications of the identified business cycle shock for its structural interpretation. (In the next section I also demonstrate the suitability of this specification for answering the question in this paper's title on the basis of evidence from a Monte Carlo experiment where the true data generating process is a state-of-the-art medium-scale DSGE model.)

Nevertheless, one may still raise the concern that my estimation could potentially be biased owing to its abstraction from theoretically sound cointegrating relations between the non-stationary variables in my VAR (e.g., stationary consumption- and investment-output ratios). There are two possible ways to address this concern. The first is to estimate the VAR in levels. Such a non-stationary specification does not come without cost: it completely disables proper inference about the long-run implications of the business cycle shock which turns out to be crucial for the structural interpretation of this shock. That said, it does have merit in demonstrating what comes out of both not taking a stand on the cointegration structure among the non-stationary variables (or lack thereof) as well as removing the long-run restriction (Restriction 2), where the latter was already done but in the context of the baseline stationary VAR (see discussion beginning on Page 21).

The second involves including in the VAR the logs of the consumption and investment shares of output, which are generally stationary in standard DSGE models and whose inclusion therefore accounts for any potential omission of theory-consistent cointegration structure. While including both ratios in real terms in place of consumption and investment also yielded results which are consistent with an IST-news-based interpretation of the business cycle shock, I proceeded with only making the former replacement (i.e., keeping investment) while adding to the VAR the nominal investment share of GDP for two reasons. The first is the clear non-stationarity of the real investment share of output for my sample. The second reason, which can be viewed as the root cause of the first reason, is that in the presence of a stochastically trending IST the real investment share of output is not stationary whereas the nominal one is (see, e.g., the model from Moura (2018) which also serves as the underlying framework of the Monte Carlo experiments of Section 5). I now turn to presenting the results from these two estimation exercises.

VAR in Levels. The results from the levels VAR appear in Figures 11a and 11b (impulse responses and FEVs) and the third and fourth rows of Table 7 (boom-bust behavior of the business cycle shock in terms of mean realizations and contribution to investment variation). Results are based on 10^6 randomly generated models from which a total of 25092 admissible models were collected.

The results appear quite similar to those from the stationary VAR without the long-run restriction (see Figures 5a and 5b and first two rows of Table 7). As in the latter case, the quantitative difference between the RPI responses across the baseline and levels VAR specification need not be taken to mean a lack of robustness; instead, they should be expected given that effectively the levels VAR specification is equivalent to the stationary VAR without the long-run restriction in terms of both specifications not being capable of revealing the truth about the long-run implications of the business cycle shock. And, still, that 44% of the 10-year variation in RPI is accounted for by the business cycle shock along with a significant boom-bust behavior in the late 1990s-early 2000s period is consistent with an IST-news-based interpretation of the business cycle shock also in the levels VAR specification.

Including Consumption and Investment Shares of Output. The results from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio are shown in Figures 12a and 12b and the sixth and fifth to last rows of Tables 1, 2, and 3. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output). Note that the response of consumption is constructed as the sum of the responses of output and the real consumption share of output, which in turn allows me to impose the baseline impact restriction and two-year 50% FEV restriction on consumption. Results are based on 10^6 randomly generated models from which a total of 252 admissible models were collected.

The results are similar to the baseline ones, with the IST-news-based interpretation of the business cycle shock continuing to be valid. This is encouraging in alleviating the concern that not accounting for theory-consistent cointegration has meaningful consequences for my results.

4.6 Fernald (2014)'s Investment TFP Measure

In addition to providing an aggregate utilization-adjusted TFP series, Fernald (2014) also constructs quarterly sectoral TFP series which are in turn based on an equality between RPI and IST that yields non-utilization-adjusted sectoral TFP measures. Effectively, the ratio between the non-utilization-adjusted consumption and investment TFP measures from Fernald (2014) is simply the ratio of investment prices, where the investment sector corresponds to consumer durables and equipment and intellectual property investment, to consumption prices with the consumption sector defined as everything that is not in the investment sector. As with the aggregate TFP measure, Fernald (2014) also provides utilization-adjusted sectoral TFP measures with the investment TFP one potentially serving as a good proxy for IST if perfect correspondence between RPI and IST were in place. It is therefore of interest to examine the robustness of my baseline results to replacing RPI with Fernald (2014)'s utilization-adjusted investment TFP measure.

Figures 13a and 13b show the impulse responses and FEV contributions from replacing my baseline RPI measure with the aforementioned investment TFP measure; and the fourth and third to last rows of Tables 1, 2, and 3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 906 admissible models were collected.

The baseline results are clearly robust to this replacement, with most of the long-run variation in the investment TFP measure being accounted for by the business cycle shock and the latter continuing to exhibit a significant boom-bust pattern in the late 1990s-early 2000s period.

4.7 Alternative Inflation Measure

The fall in inflation that takes place in response to the business cycle shock is an interesting result informing us that the business cycle shock does not appear to be a *pure* demand shock. To have more confidence in this result, it could prove useful to examine the robustness of this inflation decline to using an alternative common measure of inflation based on the personal consumption expenditures (PCE) deflator. (The Federal Reserve actually states its goal for inflation in terms of the PCE deflator.)

Figures 14a and 14b show the impulse responses and FEV contributions from replacing my baseline CPI-based inflation measure with the PCE-deflator-based inflation measure (defined as log-first-differences of the PCE deflator); and the last two rows of Tables 1, 2, and 3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 1427 admissible models were collected.

The baseline results are robust to this replacement, with this alternative inflation measure also significantly falling in response to the business cycle shock. Moreover, the long-run behavior of RPI and the boom-bust nature of the business cycle shock in the late 1990s-early 2000s period continue to hold also for this alternative specification.

5 Is the Question In the Title Answered?

One may argue that the results shown so far, although being supportive of the notion that IST news shocks are the dominant driving force behind business cycles, are also potentially consistent with a data generating process (DGP) in which there is no single comovement-producing shock driving the bulk of economic fluctuations. In other words, the argument goes, it still could be the case that this paper's identification approach may have picked up a combination of shocks, rather than a single one, thus leaving the question posed in this paper's title inconclusively answered.

In what follows, I present evidence from two Monte Carlo experiments based on an appropriate DSGE model with endogenous RPI. In the first experiment, I apply my identification approach to artificial data generated from a DGP where IST news shocks do not conform to the definition of a business cycle shock in their not producing comovement. In the second experiment I use a DGP where IST news shocks comply with the identification restrictions from 1. (I accommodate these two rather different DGPs by utilizing two different parameterizations of the same structural framework, which is based on the elaborate model structure from Moura (2018). The details of the model appear in Appendix B; below I just describe it in general terms.) Taken together, the evidence from these two experiments bolsters the empirical results shown so far in alleviating the above-mentioned concern about their potential spuriosity and accordingly enhancing confidence in their ability to provide a positive answer to the question in this paper's title.

5.1 Monte Carlo Experiment: A Model where IST News Do Not Produce Comovement

Objective. The objective of the experiment of this Section is to demonstrate what my identification approach yields when the true DGP contains IST news shocks that fail to induce comovement. Specifically, I use a DSGE model where TFP news and monetary policy shocks produce comovement but neither of them explains more than 25% of the two-year variation in output, while IST news shocks explain the majority of the latter variation but fail to produce comovmement. Understanding what follows from my identification approach in this type of setting is important for alleviating the concern that this paper's results are merely an outcome of identifying a combination of shocks.

Structural Model. Given that much focus has been placed on RPI behavior in interpreting this paper's results, and also in imposing structural discipline on the identification of the business cycle shock, it is important to use a model that properly accounts for RPI endogeneity. Toward this end, I use the two-sector DSGE model from Moura (2018) augmented with news shocks to TFP and IST which are defined as in Equations (2) and (3) with the anticipation horizon set to $j = 1$ and the smoothness parameter set to $\kappa = 0.6$. While the results I present below are robust to alterations of this baseline calibration, it serves as a sound baseline choice given the previous research that used these types of stochastic processes to define news shocks (see, e.g., Leeper and Walker (2011), Leeper et al. (2013), and Barsky and Sims (2011, 2012)).

The model is effectively an extension of the standard medium-scale sticky-price model from Smets and Wouters (2007) to an explicit two-sector structure augmented with reallocation frictions in production factors. (To keep the exposition minimal here, I defer the reader to Appendix B for a detailed description of the model.) These frictions, coupled with sector-specific price- and wage-stickiness as well as non-identical sectoral production functions, generate a wedge between RPI and IST which Moura (2018) estimates to be significant in the data even at medium horizons. Importantly, however, in the long run this wedge vanishes, in accordance with the common long-run restriction on RPI-IST equivalence used in papers attempting to identify unanticipated IST shocks (see, e.g., Fisher (2006) and Canova et al. (2010)).[30] As already discussed in Section 2.1, my allowing for the presence of IST news shocks as potential drivers of long-run RPI variation in addition to the standard surprise IST shock yields a less restrictive, more model-consistent long-run restriction.

The calibration of the model from Appendix B appears in Tables B.1 (non-shock related parameters) and B.2 (shock related parameters) and broadly follows Moura (2018)'s estimated parameters' mode posterior values as well as his non-estimated, calibrated ones. For the standard deviations of the IST and TFP news shocks, I choose a calibration that allows for IST news shocks to explain 57% of the two-year variation in output and a corresponding 21% share for TFP news shocks. Figures 15a and 15b, which depict the impulse responses and FEV contributions for IST news, TFP news, and monetary policy shocks, demonstrate that TFP news shocks produce positive impact comovement among the real aggregates (as so do monetary policy shocks, but these account for a negligible share of output variation) whereas IST news shocks only raise consumption while reducing output and investment.[31] This kind of setting, while stressing the difficulty of estimated state-of-the-art medium-scale DSGE models to produce business cycle driving IST news shocks, is valuable for my purposes as it constitutes a litmus test for my identification approach to avoid erroneously picking up a business cycle shock when one is not present in the true model.

Specifically, one may worry that such a setting would have my identification approach erroneously pick up a combination of comovement-producing shocks (TFP news and monetary policy shocks in this setting) and a dominant IST news shock (in terms of its FEV contributions, which are 57%, 63%, and 89% for the two-year variation in output, investment, and hours, respectively). This worry is based on the notion that the comovement-producing shocks comply with the comovement restriction part of identification restriction 1, whereas the dominance of the IST news shock complies with its FEV restriction part; hence, my identification procedure would possibly

[30]This long-run restriction also holds in the real and nominal models from Katayama and Kim (2018a,b), both of which have endogenous RPI owing to factor reallocation frictions with the latter paper also adding on top of that price stickiness.

[31]As discussed in Moura (2018), price stickiness in the investment sector seems to be the main driver of the inability of unanticipated IST shocks to produce positive comovement, which is also naturally related to the corresponding failure of IST news shocks to do this. Section B.10 in Appendix B discusses in more detail this failure as well as what calibration changes can be done to avoid it.

pick up TFP news and monetary policy shocks to meet the comovement restriction, while picking up IST news shocks to meet the FEV restrictions and leaving us with some combination of three structural shocks. I now turn to describing the Monte Carlo experiment and its associated results, which I use as a basis for alleviating this concern.

Data Simulation. The Monte Carlo experiment is conducted as follows. I generate 100 artificial data sets from the model from Appendix B with a sample size of 235 observations and apply my identification procedure (based on 10^5 posterior draws) involving Restrictions 1 and 2 to each artificial data set using a VAR that is identical to the baseline empirical VAR. Since the model is solved via log-linearization around the steady state, I add the model-consistent steady state growth rates to the simulated non-stationary variables as well the steady state values to the simulated stationary variables. To gain an understanding as to the importance of imposing the long-run restriction (Restriction 2) in my analysis, I present results for two cases: *i*) the baseline case, where I impose both Restriction 1 and Restriction 2 when applying my estimation procedure to the artificial data sets and *ii*) an alternative case, where I only impose Restriction 1.

Baseline Case. The first row of Table 10 presents the share of simulations in which identification was null along with the average admissibility rate (average number of admissible models divided by total number of posterior draws (10^5)) for the simulations that did produce a non-null set of admissible models, where both Restriction 1 and Restriction 2 are imposed in the identification procedure. Ideally, one would want to see that in all simulations a zero admissibility rate obtains, i.e., null set of identified models for all simulations, as this would strongly support the capacity of my indication procedure to avoid spurious identification. As shown Table 10, the results are very close to ideal: 96 out of the 100 simulations lead to a null set of identified models and for the 4 simulations which do not there is an average admissibility rate that is much lower than its baseline empirical counterpart reported on Page 13 (1.75×10^{-5} compared to 129.7×10^{-5}).[32] In

[32]Importantly, one need be careful in considering the size of the set of admissible models as an indication for the validity of the identification restrictions. As Kilian and Lutkepohl (2017) point out in Chapter 13, the estimates of sign-identified models are conditional on the chosen identifying assumptions which are in turn *not testable* within the SVAR framework. (To see this, consider an asymptotic world where the reduced form VAR is perfectly estimated and also assume that identifying restrictions are correct. In this

fact, in three of the non-null four simulations, only one admissible model was identified out of 10^5 posterior draws with the remaining simulation yielding a set of only 4 admissible models. Overall, the findings from the first row of Table 10 indicate that it is very unlikely that my identification procedure would spuriously identify a business cycle shock if the true model contained several shocks that individually comply with only part of my procedure's identification restrictions.

Removing the RPI Long-Run Restriction. The second row of Table 10 presents the share of simulations in which identification was null along with the average admissibility rate for the simulations that did produce a non-null set of admissible models, only now from only imposing Restriction 1 in the estimations. The risk of spurious identification seems low also in this case, with only 15% of the simulations resulting in non-null identification. However, this risk is still much greater than that observed for the baseline estimation case (nearly 4 times as much). This emphasizes one dimension of the added value from imposing Restriction 2, which is related to the significantly reduced risk of spurious identification when the true DGP does not contain a single business cycle shock. The other dimension, which is related to the added value from doing so when the true DGP *does* contain a single business cycle shock, is discussed in the next section. Lastly, it is also worthwhile noting that, given the much higher admissibility rate observed in actual data when applying my estimation procedure without imposing Restriction 2, the very low admissibility rate reported in the second row of Table 10 (2.67×10^{-5}) is also not supportive (like that from the first row) of the notion that it is likely that the true DGP behaves similarly to that implied by the DSGE model at hand.

kind of world there is only one impact matrix compatible with the reduced form VAR, i.e., upon applying an estimation algorithm such as mine one should get one admissible model.) I am merely using the size of the set of admissible models here to highlight that the stark differences between actual and Monte Carlo based admissibility rates are not supportive of the notion that it is likely that the true DGP corresponds to the DSGE model at hand, i.e., a model where there is no single business cycle shock but a combination of shocks individually complying only in part with my identification restrictions.

5.2 Monte Carlo Experiment: A Model where IST News Shocks Comply With Restriction 1

Objective. The evidence from the previous section was based on a true DGP that delivers only partial compliance of the IST news shock with the identification restrictions of my estimation procedure. Such a setting proved informative in showing the fairly strong capacity of my identification procedure to avoid spuriously identifying a business cycle shock when such a shock does not exist. This section aims at accomplishing a complementary objective in showing that my identification procedure can be successful in picking up a business cycle shock when such a shock truly exists in the true DGP.

Structural Model. To obtain the aformentioned goal, one needs a DSGE model with comovement-producing IST news shocks. However, this turns out to be quite a challenge in the context of estimated models. E.g., while employing the calibration used in Jaimovich and Rebelo (2009) generates positive business cycle comovement in response to IST news shocks, using the estimated parameters obtained in Khan and Tsoukalas (2011) (who embedded the preference structure from Jaimovich and Rebelo (2009) into a medium-scale DSGE model) does not deliver similar impulse responses. And, importantly, such estimated parameters do not produce significant FEV contributions for IST news shocks. The estimated, elaborate two-sector model of Moura (2018) is no exception in this regard as IST news shocks fail to produce positive comovement in his model (see Figure 15a). Hence, to maintain the appealing structural framework of Moura (2018) while still encompassing IST news shocks that comply with Restrictions 1 and 2, one must alter the calibration of this model's parameters.

Since my objective in this section is to produce a DSGE model based DGP with IST news shocks that comply with Restrictions 1 and 2, but also at the same time maintain a reasonable calibration in terms of data fit and previous research, I try to alter as few as possible parameters' values. That said, in weighing the tradeoff between consistency with the DSGE literature and being able to obtain a suitable DGP for the sake of the sought after Monte Carlo experiment of this section, I place a much larger weight on the latter. To keep the exposition here minimal, I defer the discussion on the specific calibration alterations I make to Section B.10 in Appendix B.[33] I now turn to discussing the results from the Monte Carlo experiment, again separating them into those obtained from imposing Restriction 2 in addition to 1 and those obtained from removing long-run Restriction 2.

Baseline Case. As in the previous section, I simulate 100 artificial data sets from the model and apply to each my estimation procedure where 10^5 posterior draws are taken in the Bayesian estimation. My focus is on comparing the average of the estimated median and 84th and 16th percentiles of the impulse responses and FEV contributions posterior distribution, where the average is taken over the 100 Monte Carlo simulations, to their corresponding theoretical counterparts from the model. Figures 16a and 16b show the mean estimated median and 84th and 16th percentile impulse responses and FEV contributions to the variables' variation of the identified business cycle shock over a ten year horizon, along with the corresponding true responses and contributions from the true model. It is apparent that the mean estimated median responses are quite close to their theoretical counterparts, especially at business cycle frequencies.[34] In accordance with this, the mean correlation between the estimated median business cycle shock series and the true IST news shock series is 90%.

It is also clear that at longer horizons there is a downward bias in the estimates of the non-stationary variables' impulse responses. Nevertheless, the estimated long-run effect on RPI (not shown in the figures) is still informative in facilitating the correct interpretation of the business cycle shock as an IST news shock, in terms of both the impulse responses and the FEVs with the

[33] I make 5 parameter calibration changes with respect to Table B.1 to induce compliance of the IST news shock with the impact comovement restriction as well as an adjustment of the shocks' standard deviations such that IST news shocks account for the bulk of business cycle variation in the real aggregates while at the same time their effects are not overwhelmingly large. Some sacrifice was made particularly in terms of the RPI and investment responses, which are too large at longer horizons (also see Figure 15a in the context of the baseline calibration, in which hours response at short horizons is also too large); but this cost is worthwhile incurring given the main purpose of the Monte Carlo experiment of this section which is to examine the capacity of my identification procedure to properly identify the business cycle shock when such a shock exists in a state-of-the-art structural framework.

[34] Note that the true effect of IST news shocks on TFP is zero all horizons. I have experimented with DGPs where IST news shocks are allowed to have a meaningful delayed effect on TFP, as in the data, and found that these effects are also captured well by my identification procedure. To keep the experiment as simple as possible, I abstract from such effects in the Monte Carlo experiments presented here.

former mean median estimate being -4.4% and the latter being 70.2%. Also worthwhile noting is the downward bias in the estimates of the FEVs from Figure 16b,[35] which indicates that the empirical results of this paper can be seen as potentially conservative with respect to the true role of IST news shocks. Overall, it is clear that my identification procedure does a good job of identifying the business cycle shock as an IST news shock when such a correspondence truly exists in the DGP.

In the third row of Table 10 I also present the share of simulation with null identification along with the corresponding admissibility rates. Clearly, this Monte Carlo experiment does not lead to any problem relating to null identification as was the case in the previous section. While the mean admissibility rate is somewhat lower than its empirical counterpart (78.2×10^{-5} compared to 129.7×10^{-5}), over 25% of the simulations resulted in an admissibility rate of at least 100×10^{-5}, which is quite comparable to the empirical one; and 13% of them had an admissibility rate that exceeded the empirical one. Furthermore, I also found that the Monte Carlo based admissibility rates are increasing in the dominance of the IST news shock it terms of the real aggregates' FEV it accounts for, which supports the notion that the results of this paper are likely the outcome of a correct identification. Put differently, taken together with both the results from the previous section as well as the empirical ones, the results of this section highlight that it is very unlikely that a spurious identification of the business cycle shock is what is standing behind the empirical results of this paper.

Removing the RPI Long-Run Restriction. I now present results from the same experiment underlying Figures 16a and 16b, only that now I only impose Restriction 1 when applying my estimation procedure to the artificial data sets. Figures 17a and 17b present the results from this Monte Carlo experiment. While the mean estimated median responses and FEV contributions for RPI and TFP are reasonably close to their theoretical counterparts at short-run horizons and the mean correlation between the estimated median IST news shock series and the true IST news shock series is similar to that obtained from also imposing Restriction 2 (91%), there is a very large

[35] The only exception is the FEV estimate for TFP which is upward biased. Nevertheless, as is clear from the first sub-figure of Figure 16a, the zero effect on TFP is reasonably captured especially as the horizon advances.

downward bias in the estimated long-run effect and FEV contribution for RPI (not shown in the figures) with these standing at -2.5% and 36%. The latter significantly downward biased FEV estimate, which is roughly half of the corresponding estimate from also imposing Restriction 2 in the estimation procedure, makes it clear that there is an important cost resulting from not imposing the RPI long-run restriction in terms of properly identifying the long-run implications of the business cycle shock. Moreover, this estimated FEV number accords reasonably well with its empirical counterpart obtained when only imposing Restriction 1 to actual data. Overall, the results shown so far for this experiment raise confidence in the notion that the true DGP underlying the results of this paper is one where the business cycle shock is an IST news shock.

The fourth row of Table 10 presents the share of simulation with null identification along with the corresponding mean admissibility rate. Here too there is no problem of null identification, which one should expect given the existence of a business cycle shock in the true DGP. Moreover, the mean admissability rate is roughly similar to its empirical counterpart. (Note that the much larger admissability rate obtained for this less restrictive estimation procedure relative to the baseline estimation stresses the relevance of the point raised in Footnote 32 that one need not use the size of the set of admissible models as an indication for the identifying restrictions' validity.) Hence, taken together with the results from the previous section, both the third and fourth rows of Table 10 accord well with the notion that it is very unlikely that a spurious, rather than correct, identification of the business cycle shock is what has generated the empirical results of this paper.

6 Conclusion

This paper has provided robust evidence in favor of GPT news shocks being the major driver behind business cycle fluctuations, where the manifestation of these anticipated GPT shocks takes place in the investment-specific goods sector through IST news shocks. To obtain this evidence, I first computed the set of models in which one shock generates business cycle comovement, i.e., raises output, hours, consumption, and investment on impact, and explains over 50% of the business cycle variation in the latter real aggregates. Then, I examined the common features of this business cycle shock across the models and found that this shock encompasses two robust characteristics: *i*) it drives the bulk of the long-run variation in RPI and has a significant long-run effect on TFP, reducing the former and raising the latter; and *ii*) it behaves in a boom-bust manner in the late 1990s and early 2000s period, exhibiting significant positive realizations in the former period while experiencing negative realizations in latter period. The first characteristic allows to determine that the shock is likely a GPT shock, represented by either an unanticipated IST shock or an IST news shock, which leads to long-term TFP gains by generating delayed fundamental changes in the production process of the sectors using the new IST-related goods, whereas the second feature allows to deduce that it is an IST news shock given the common view of the late 1990s and early 2000s as having been driven by favorable expectations about IST that were later revised downwards.

Importantly, the results of this paper were obtained using a rather agnostic approach that does not attempt to identify, ex-ante, any particular shock but rather lets the data indicate whether there is a single, structural shock that drives the bulk of economic fluctuations. As such, this identification approach is arguably more reliable because the identifying assumptions underlying it are inherently weak. It is my hope that this paper's results will provide a guide to future model builders in focusing attention on constructing business cycle models where IST news shocks are the central force behind economic fluctuations and are intrinsically related to future GPT changes that translate to long-term TFP gains.

Appendix A Bayesian Estimation Procedure

The VAR given by (4) can be written in matrix notation as follows:

$$Y = XB + U \tag{A.1}$$

where $Y = [y_1, ..., y_T]'$, $X = [X_1, ..., X_T]'$, $X_t = [y_{t-1}, ..., y_{t-p}, 1]'$, $B = [B_1, ..., B_p, B_c]'$, k and p are the number of variables and lags, respectively, and $U = [u_1, ..., u_T]'$. B here represents the reduced form VAR coefficient matrix and Σ is the variance-covariance matrix of the reduced form VAR innovations. I follow the conventional approach of specifying a normal-inverse Wishart prior distribution for the reduced-form VAR parameters:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_0), \Sigma \otimes N_0^{-1}), \tag{A.2}$$

$$\Sigma \sim IW_k(v_0 S_0, v_0), \tag{A.3}$$

where N_0 is a kpxkp positive definite matrix, S_0 is a kxk covariance matrix, and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_T), \Sigma \otimes N_T^{-1}), \tag{A.4}$$

$$\Sigma \sim IW_k(v_T S_T, v_T), \tag{A.5}$$

where $v_T = T + v_0$, $N_T = N_0 + X'X$, $\bar{B}_T = N_T^{-1}(N_0\bar{B}_0 + X'X\hat{B}), S_T = \frac{v_0}{v_T} S_0 + \frac{T}{v_T}\hat{\Sigma} + \frac{1}{v_T}(\hat{B} - \bar{B}_0)' N_0 N_T^{-1} X'X(\hat{B} - \bar{B}_0)$, $\hat{B} = (X'X)^{-1}X'Y$, and $\hat{\Sigma} = (Y - X\hat{B})'(Y - X\hat{B})/T$.

I follow the sign restrictions literature and use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary S_0 and $\bar{B}_0$. This implies that the prior distribution is proportional to $|\Sigma|^{-(k+1)/2}$ and that $v_T = T$, $S_T = \hat{\Sigma}$, $\bar{B}_T = \hat{B}$, and $N_T = X'X$.

It is further assumed that there exists a linear mapping between the reduced-form innovations and economic shocks, e_t, given by

$$u_t = Ae_t. \tag{A.6}$$

The impact matrix A must satisfy $AA' = \Sigma$. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, C (e.g, the

Cholesky factor of Σ), the entire space of permissible impact matrices can be written as CD, where D is a k x k orthonormal matrix (i.e., $D' = D^{-1}$ and $DD' = I$, where I is the identity matrix). I follow the efficient method proposed by Rubio-Ramirez et al. (2010) for generating orthonormal matrices Ds and the associated identification, impact A matrices.

Formally, the posterior simulator for $\{B,\Sigma,D\}$) can be described as follows:

1. Draw Σ from an $IW_k(T\hat{\Sigma}, T)$ distribution.
2. Draw B from the conditional distribution $MN(\hat{B}, \Sigma \otimes (X'X)^{-1})$.
3. Draw D using the algorithm from Rubio-Ramirez et al. (2010) and compute the impact Matrix $A = CD$ where C is the Cholsky factor of Σ; then, use the matrix triplet $\{B,\Sigma,D\}$ to compute the impulse response function and forecast error variance contributions of e_t.
4. Keep $\{B,\Sigma,D\}$ if Restrictions 1 and 2 are met.
5. Repeat steps 1-4 a large number of times and collect the drawn $\{B,\Sigma,D\}$'s.

Appendix B Model

This appendix lays out a two-sector medium-scale DSGE model whose structure builds on Moura (2018), who extended the Smets and Wouters (2007) framework into an explicit two-sector structure that accommodates non-identical sector-specific production functions, sector-specific price and wage stickiness, and labor and capital reallocation frictions. Abstracting from these three elements altogether would result in perfect correspondence between RPI and IST at all horizons, while their presence results only in a long-run quantitative equivalence between RPI and IST. Hence, this modeling framework is suitable for my purposes as it accounts for RPI endogeneity in a structural manner and thus constitutes a valuable lens through which to examine the suitability of my identification procedure for answering the question posed in this paper's title. The main difference between my framework and that of Moura (2018) lies in my adding to the latter news shocks to both TFP and IST.

The general setup for both the consumption and investment sectors is very similar, with the only difference between them being the introduction of IST for the modeling of the investment sector. In what follows below I present the main building blocks of the model.

B.1 Households

There is a continuum of optimizing households, indexed by $j \in [0,1]$, that maximize their lifetime utility subject to their inter-temporal budget constraint and the sector-specific capital accumulation constraints by choosing consumption bundle $C_t(j)$; hours worked in the consumption sector $L_t^C(j)$ and hours worked in the investment sector $L_t^I(j)$, where the aggregate level of hours worked for each household is defined as $L_t(j) = \left[(L_t^C(j))^{1+\tau} + (L_t^I(j))^{1+\tau}\right]^{\frac{1}{1+\tau}}$ with $\tau \geq 0$; one-period securities bonds $B_{t+1}(j)$ with price equal to the inverse of next period's risk-free interest rate $(1/R_{t+1})$; investment bundle $I_t(j)$; next period's installed capital in the consumption sector $K_{t+1}^C(j)$ and corresponding installed capital in the investment sector $K_{t+1}^I(j)$; and capital utilization rate $u_t(j)$ where the aggregate level of capital services for each household is defined as $K_{t+1}^s(j) = \left[(K_{t+1}^{s,C}(j))^{1+\nu} + (K_{t+1}^{s,I}(j))^{1+\nu}\right]^{\frac{1}{1+\nu}}$ with $\nu \geq 0$ and $K_{t+1}^s(j) = u_t(j)K_{t+1}(j)$, $K_{t+1}^{s,C}(j) = u_t(j)K_{t+1}^C(j)$, $K_{t+1}^{s,I}(j) = u_t(j)K_{t+1}^I(j)$. Formally, this maximization problem can be written as

$$
\begin{aligned}
&\max_{\left\{\substack{C_t(j),L_t^C(j),L_t^I(j),B_{t+1}(j),I_t(j),\\ K_{t+1}^C(j),K_{t+1}^I(j),K_{t+1}^I,(j)u_t(j)}\right\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \zeta_t \left[\frac{(C_t(j) - hC_{t-1})^{1-\sigma_c}}{1-\sigma_c} exp\left(\frac{\sigma_c - 1}{1+\sigma_l}\left[(L_t^C(j))^{1+\omega} + (L_t^I(j))^{1+\omega}\right]^{\frac{1+\sigma_l}{1+\omega}}\right)\right] \\
&s.t \;\; C_t(j) + RPI_t I_t(j) + \frac{B_{t+1}(j)}{R_{t+1}P_t^C} - T_t \leq \frac{B_t(j)}{P_t^C} + \frac{W_t^{w,C}L_t^C(j) + W_t^{w,I}L_t^I(j)}{P_t^C} + \\
&\quad + RPI_t\left[R_t^{K,C}u_t^C(j)K_t^C(j) + R_t^{K,I}u_t(j)K_t^I(j) - \psi(u_t(j))K_t^C(j) - \psi(u_t(j))K_t^I(j)\right] + \frac{Div_t}{P_t^C}, \qquad \text{(B.1)} \\
&\quad K_{t+1} = (1-\delta)K_t + \left[1 - \Upsilon\left(\frac{I_t}{I_{t-1}}\right)\right] I_t, \\
&\quad K_{t+1}^s(j) = \left[(K_{t+1}^{s,C}(j))^{1+\nu} + (K_{t+1}^{s,I}(j))^{1+\nu}\right]^{\frac{1}{1+\nu}}, \\
&\quad K_{t+1}^s(j) = u_t(j)K_{t+1}(j) \;\; K_{t+1}^{s,C}(j) = u_t(j)K_{t+1}^C(j) \;\; K_{t+1}^{s,I}(j) = u_t(j)K_{t+1}^I(j),
\end{aligned}
$$

where ζ_t is an intertemporal preference shock; h is the external habit formation parameter; σ_c is the inverse elasticity of inter-temporal substitution; σ_l is the inverse Frisch elasticity of labor supply; T_t are lump-sum taxes; $W_t^{h,x}$ is hourly wage paid to households for working in sector x, with $x = C, I$; $K_t^{s,x}(j) = u_t(j)K_t^x(j)$ is capital services used in production in sector x, where $u_t^x(j)$ is the sector-specific capital utilization rate and $K_t^x(j)$ is sector-specific installed capital; RPI_t represents the relative price of investment, i.e., $\frac{P_t^I}{P_t^C}$, where P_t^C and P_t^I are the prices of consumption and investment bundles $C_t(j)$ and $I_t(j)$, respectively; $RPI_t R_t^{K,x} u_t^x(j) K_t^x(j)$ is income earned from renting capital from sector x with $R_t^{K,x}$ denoting the rental rate of capital services in sector x and $\psi(u_t(j))K_t^x(j)$ representing the resource cost of increasing the rate of capital utilization in sector x;[36] Div_t denotes total dividends distributed by imperfectly competitive retail firms and labour unions in the economy; Υ is the investment adjustment cost function, with $\Upsilon(\gamma) = \Upsilon'(\gamma) = 0$ and $\Upsilon''(\cdot) > 0$;[37] and δ is the capital depreciation rate.

Importantly, as in Horvath (2000), the above specification of the disutility of working implies imperfect labor mobility across sectors when $\omega > 0$, allowing for sectoral heterogeneity in wages and hours worked. And the similar specification of the aggregation of capital across sectors introduces frictions in the sectoral reallocation of capital.

B.2 Intermediate Labor Union Sector and Labor Packers

There is a continuum of intermediate sector-specific labor unions, that differentiate the labor services supplied by households and sell them to *labor packers* who then package and resell them to intermediate goods producers. It is assumed that these labor unions set nominal wages subject to Calvo frictions and that each labor union represents a different labor service; I index the continuum of these labor services by $l \in [0, 1]$.

Labor Packers. The labor packers in sector x, with $x = C, I$, maximize profits subject to a Dixit and Stiglitz (1977) aggregator:

$$\begin{aligned} &\max_{L_t^x, L_t^x(l)} W_t^x L_t^x - \int_0^1 W_t^x(l) L_t^x(l) dl \\ &s.t \;\; L_t^x = \left[\int_0^1 L_t^x(l)^{\frac{\phi^{w,x}-1}{\phi^{w,x}}} dl \right]^{\frac{\phi^{w,x}}{\phi^{w,x}-1}} , \end{aligned} \tag{B.2}$$

[36] I assume the following capital utilization cost function: $\psi(u_t(j)) = \frac{\omega}{2}(u_t(j) - 1)^2$.

[37] I assume the following investment adjustment cost function: $\Upsilon\left(\frac{I_t}{I_{t-1}}\right) = \frac{\varpi}{2}\left(\frac{I_t(j)}{I_{t-1}(j)} - 1\right)^2$.

where W_t^x and $W_t^x(l)$ are the prices of the composite and intermediate sector-specific labor services, respectively, and $\phi^{w,x} > 1$ the sector-specific elasticity of substitution among the different labor services. Combining the FOCs of Problem (B.2) gives

$$L_t^x(l) = L_t^x \left(\frac{W_t^x(l)}{W_t^x} \right)^{-\phi^{w,x}}. \tag{B.3}$$

Labor Unions. Sector-specific nominal wage rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: unions in sector x have market power and can readjust wages with probability $1 - \xi_{w,x}$ in each period; for those unions that cannot readjust, $W_t^x(l)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,C}$ (i.e., $\frac{P_{t-1}^C}{P_{t-2}^C}$). The optimal wage set by the union that is allowed to re-optimize its wage is obtained from solving the following optimization problem:

$$\begin{aligned} &\max_{\widetilde{W}_t^x(l)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{w,x}^{t+s} \frac{\beta^{t+s}\Xi_{t+s}P_t^C}{\Xi_t P_{t+s}^C} \left[W_t^x(l) - W_{t+s}^{h,x} \right] L_{t+s}(l) \\ s.t\;\; &L_t^x(l) = L_t^x \left(\frac{W_t^x(l)}{W_t^x} \right)^{-\phi^{w,x}}, \\ &W_t^x(l) = \widetilde{W}_0^x(l) \prod_0^t \pi_{t,C}^{\iota_{w,x}}, \end{aligned} \tag{B.4}$$

where $\widetilde{W}_t^x(l)$ is the newly set wage; $\xi_{w,x}$ is the Calvo (1983) probability of being allowed to optimize one's wage; $\frac{\beta^{t+s}\Xi_{t+s}}{\Xi_t P_{t+s}}$ is the nominal discount factor for households, where $\Xi_t = \zeta_t (C_t - hC_{t-1})^{-\sigma_c}$ $exp\left(\frac{\sigma_c - 1}{1+\sigma_l} \left[(L_t^C(j))^{1+\omega} + (L_t^I(j))^{1+\omega} \right]^{\frac{1+\sigma_l}{1+\omega}} \right)$; and $0 \leq \iota_{w,x} < 1$ is the parameter governing the partial indexation mechanism.

B.3 Final Good Firms

The sector-specific final good Y_t^x ($x = C, I$) is produced by final good firms as a composite made of a continuum of sector-specific intermediate goods, indexed by $i \in [0, 1]$. The final good is supplied to consumers, investors, and the government, and is purchased in a monopolistically competitive market from the intermediate goods firms, at monopolistic price $P^x(i)$.

All final good firms have access to a technology that allows them to transform intermediate goods into final goods via a Dixit and Stiglitz (1977) aggregator, leading to the following maximization problem facing final good firms:

$$\begin{aligned} &\max_{Y_t, Y_t(i)} P_t^x Y_t^x - \int_0^1 P_t^x(i) Y_t^x(i) di \\ &s.t\ \ Y_t^x = \left[\int_0^1 Y_t^x(i)^{\frac{\phi^{p,x}-1}{\phi^{p,x}}} di \right]^{\frac{\phi^{p,x}}{\phi^{p,x}-1}} \quad , \end{aligned} \tag{B.5}$$

where P_t^x and $P_t^x(i)$ are the prices of the composite and intermediate produced goods in sector x, respectively, and $\phi^{p,x} > 1$ is the elasticity of substitution among the different goods. Combining the FOCs of Problem (B.5) gives

$$Y_t^x(i) = Y_t^x \left(\frac{P_t^x(i)}{P_t^x} \right)^{-\phi^{p,x}}. \tag{B.6}$$

B.4 Intermediate Goods Producers

There is a continuum of intermediate goods producers in both the consumption and investment sectors that produce good Y_t^x. Since the only effective asymmetry between the modeling of these two sectors lies in the technology used to produce the intermediate good, I proceed in this section by separately presenting the modeling of each sector's intermediate goods producers.

Consumption Sector. The intermediate goods producers in the consumption sector produce good $Y_t^C(i)$ using the following technology:

$$Y_t^C(i) = A_t K_t^{s,C}(i)^{\alpha_C} L_t^C(i)^{1-\alpha_C} - \varphi_t^C, \tag{B.7}$$

where A_t represent TFP in the economy; $K_t^{s,C}(i) = u_t(i) K_t^C(i)$ is capital services used in production, where $u_t(i)$ is the capital utilization rate and $K_t^C(i)$ is installed capital; $L_t^C(i)$ is the labor input; and φ_t^C is a deterministic fixed production cost with a trend that is included to ensure proper scaling of the fixed cost. I assume that intermediate goods producers are perfectly competitive in the input markets; they minimize costs by choosing L_t^C and $K_t^{s,C}$, taking wages and capital services rental rates as given, subject to the production function (B.7):

$$\begin{aligned} &\min_{L_t^C(i), K_t^{s,C}(i)} W_t^C L_t^C(i) - R_t^{k,C} K_t^{s,C}(i) \\ &s.t\ \ Y_t^C(i) = A_t K_t^{s,C}(i)_C^{\alpha} L_t^C(i)^{1-\alpha_C} - \varphi_t^C, \end{aligned} \tag{B.8}$$

which yields the following FOCs:

$$(\partial L_t^C): \quad \Theta_t^C(i)(1-\alpha_C)A_t K_t^{s,C}(i)_C^{\alpha} L_t^C(i)^{-\alpha_C} = W_t^C, \tag{B.9}$$

$$(\partial K_t^{s,C}): \quad \Theta_t^C(i)\alpha_C A_t K_t^{s,C}(i)^{(\alpha_C-1)} L_t^C(i)^{(1-\alpha_C)} = R_t^{k,C}, \tag{B.10}$$

where Θ_t is the Lagrange multiplier associated with the production function and equals marginal cost MC_t^C, which is the same for all firms in the consumption sector and whose expression can be written as

$$MC_t^C = \frac{1}{A_t} W_t^{C\,1-\alpha_C} (R_t^{k,C})^{\alpha_C} \alpha_C^{-\alpha_C} (1-\alpha_C)^{(-1-\alpha_C)}. \tag{B.11}$$

Nominal price rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: retail firms can readjust prices with probability $1-\xi_{p,C}$ in each period; for those firms that cannot readjust, $P_t^C(i)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,C}$. The optimal price set by the firm that is allowed to re-optimise its price is obtained from solving the following optimization problem:

$$\begin{aligned} &\max_{\widetilde{P}_t^C(i)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{p,C}^{t+s} \frac{\beta^{t+s}\Xi_{t+s}P_t^C}{\Xi_t P_{t+s}^C} \left[P_t^C(i) - MC_{t+s}^C\right] Y_{t+s}^C(i) \\ s.t\ \ & Y_t^C(i) = Y_t^C \left(\frac{P_t^C(i)}{P_t^C}\right)^{-\phi^{p,C}}, \\ & P_t^C(i) = \widetilde{P}_0^C(i) \prod_0^t \pi_{t,C}{}^{\iota_{p,C}}, \end{aligned} \tag{B.12}$$

where $\widetilde{P}_t^C(i)$ is the newly set price, $\xi_{p,C}$ is the Calvo (1983) probability of being allowed to optimize one's price, $\frac{\beta^{t+s}\Xi_t}{\Xi_{t+s}P_{t+s}}$ is the nominal discount factor for households already defined above for Problem (B.4), $0 \leq \iota_{p,C} < 1$ is the parameter governing the partial indexation mechanism, and MC_t^C is the firm's nominal marginal cost.

Investment Sector. The intermediate goods producers in the investment sector produce good $Y_t^I(i)$ using the following technology:

$$Y_t^I(i) = A_t S_t K_t^{s,I}(i)^{\alpha_I} L_t^I(i)^{1-\alpha_I} - \varphi_t^I, \tag{B.13}$$

where A_t represent TFP in the economy; S_t is IST; $K_t^{s,I}(i) = u_t(i)K_t^I(i)$ is capital services used in production, where $u_t(i)$ is the capital utilization rate and $K_t^I(i)$ is installed capital; $L_t^I(i)$ is the labor input; and φ_t^I is a deterministic fixed production cost with a trend that is included to ensure proper scaling of the fixed cost. Apart from the presence of IST in the production function of intermediate firms in the investment sector, the modeling of these firms is prefectly symmetric with respect to that of intermediate firms in the consumption sector.

Specifically, I assume that intermediate goods producers are perfectly competitive in the input markets; they minimize costs by choosing L_t^I and $K_t^{s,I}$, taking wages and capital services rental rates as given, subject to the production function (B.7):

$$\begin{aligned} &\min_{L_t^I(i),K_t^{s,I}(i)} W_t^I L_t^I(i) - R_t^{k,I} K_t^{s,I}(i) \\ &s.t\ \ Y_t^I(i) = A_t S_t K_t^{s,I}(i)_I^{\alpha} L_t^I(i)^{1-\alpha_I} - \varphi_t^I, \end{aligned} \tag{B.14}$$

which yields the following FOCs:

$$(\partial L_t^I): \quad \Theta_t^I(i)(1-\alpha_I) A_t S_t K_t^{s,I}(i)_I^{\alpha} L_t^I(i)^{-\alpha_I} = W_t^I, \tag{B.15}$$

$$(\partial K_t^{s,I}): \quad \Theta_t^I(i)\alpha_I A_t S_t K_t^{s,I}(i)^{(\alpha_I-1)} L_t^I(i)^{(1-\alpha_I)} = R_t^{k,I}, \tag{B.16}$$

where Θ_t is the Lagrange multiplier associated with the production function and equals marginal cost MC_t^I, which is the same for all firms in the consumption sector and whose expression can be written as

$$MC_t^I = \frac{1}{A_t S_t} W_t^{I^{1-\alpha_I}} (R_t^{k,I})^{\alpha_I} \alpha_I^{-\alpha_I} (1-\alpha_I)^{(-1-\alpha_I)}. \tag{B.17}$$

Nominal price rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: retail firms can readjust prices with probability $1-\xi_{p,I}$ in each period; for those firms that cannot readjust, $P_t^I(i)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,I}$. The optimal price set by the firm that is allowed to re-optimise its price is obtained from solving the following optimization problem:

$$\begin{aligned} &\max_{\widetilde{P}_t^I(i)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{p,I}^{t+s} \frac{\beta^{t+s}\Xi_{t+s} P_t^C}{\Xi_t P_{t+s}^C} \left[P_t^I(i) - MC_{t+s}^I \right] Y_{t+s}^I(i) \\ &s.t\ \ Y_t^I(i) = Y_t^I \left(\frac{P_t^I(i)}{P_t^I} \right)^{-\phi^{p,I}}, \\ &P_t^I(i) = \widetilde{P}_0^I(i) \prod_0^t \pi_{t,I}{}^{\iota_{p,I}}, \end{aligned} \tag{B.18}$$

where $\widetilde{P}_t^I(i)$ is the newly set price, $\xi_{p,I}$ is the Calvo (1983) probability of being allowed to optimize one's price, $\frac{\beta^{t+s}\Xi_t}{\Xi_{t+s}P_{t+s}}$ is the nominal discount factor for households already defined above for Problem (B.4), $0 \leq \iota_{p,I} < 1$ is the parameter governing the partial indexation mechanism, and MC_t^I is the firm's nominal marginal cost.

B.5 Aggregate Resource Constraints

Final output in the consumption sector may either be transformed into a single type of consumption good that is consumed by households or by the government, while final output in the investment sector may either be transformed into a single type of investment good that is consumed by households or by the government, or used up through capital utilization costs. In particular, the economy-wide resource constraints for consumption and investment sectors are given by

$$Y_t^C = C_t + G_t^C, \tag{B.19}$$

$$Y_t^I = I_t + G_t^I + \psi^d(u_t)K_t, \tag{B.20}$$

where G_t^C and G_t^I represent government spending on consumption and investment goods, respectively.

Nominal GDP is defined as $P_t^C(C_t + G_t^C) + P_t^I(I_t + G_t^I)$ where, as usual, capital utilization costs are accounted for as intermediate consumption and do not show up in GDP. Real GDP (Y_t) in consumption units is then given by

$$Y_t = C_t + G_t^C + RPI_t(I_t + G_t^I). \tag{B.21}$$

B.6 Monetary Policy

There is assumed to be a central bank that follows a nominal interest rate rule by adjusting its instrument in response to deviations of consumption goods inflation from steady state inflation as well as deviations of real GDP growth rate from its steady state growth rate μ, which is equal to $\mu = \mu_A + \alpha_C\mu_S$ where μ_A and μ_S are the steady state growth rates of TFP and IST, respectively. This Taylor-like policy rule is given by the following equation:

$$\frac{R_{t+1}}{R^*} = \left(\frac{R_t}{R^*}\right)_r^{\rho} \left[(\frac{\pi_{t,C}}{\pi_C^*})^{r_\pi} \left(\frac{Y_t}{Y_{t-1}\mu}\right)^{r_y} \right]^{1-\rho_r} exp(\epsilon_t^R), \tag{B.22}$$

where R^* is the steady state nominal gross rate; parameter ρ_r determines the degree of interest rate smoothing; parameters r_π and r_y govern the strength of the responses of monetary policy to deviations of inflation and output growth from their target levels, respectively; and ϵ_R is a white noise monetary policy shock, i.e., $\epsilon_t^R \sim iid(0, \sigma_R)$.

B.7 Fiscal Policy

The government budget constraint is of the form

$$P_t^C G_t^C + P_t^I G_t^I + B_t = \frac{B_{t+1}}{R_{t+1}} + T_t, \tag{B.23}$$

where T_t are nominal lump-sum taxes that also appear in the households' budget constraint

B.8 Shocks

I include in the model a total of 8 shocks: TFP surprise and news shocks, IST surprise and news shocks, monetary policy shocks, government consumption and investment shocks, and preference shocks. The monetary policy shock, ϵ_t^R, has already been introduced above in Equation (B.22). To define the other shocks, I now introduce the following stochastic processes for their corresponding fundamentals:

$$lnA_t = \mu_A t + lnA_{t-1} + z_{t-1}^A + \epsilon_t^{A,surprise}, \ \epsilon_t^{A,surprise} \sim iid(0, \sigma_{A,surprise}); \tag{B.24}$$

$$z_t^A = \rho_{z,A} z_{t-1}^A + \epsilon_t^{A,news}, \ \epsilon_t^{A,news} \sim iid(0, \sigma_{A,news}); \tag{B.25}$$

$$lnS_t = \mu_S t + lnS_{t-1} + z_{t-1}^S + \epsilon_t^{S,surprise}, \ \epsilon_t^{S,surprise} \sim iid(0, \sigma_{S,surprise}); \tag{B.26}$$

$$z_t^S = \rho_{z,S} z_{t-1}^S + \epsilon_t^{S,news}, \ \epsilon_t^{S,news} \sim iid(0, \sigma_{S,news}); \tag{B.27}$$

$$lnG_t^C = \mu t + \rho_{G,C} lnG_{t-1}^C + \epsilon_t^{G,C}, \ \epsilon_t^{G,C} \sim iid(0, \sigma_{G,C}); \tag{B.28}$$

$$lnG_t^I = \mu_S t + \rho_{G,I} lnG_{t-1}^I + \epsilon_t^{G,I}, \ \epsilon_t^{G,I} \sim iid(0, \sigma_{G,I}); \tag{B.29}$$

$$ln\zeta_t^I = \rho_\zeta ln\zeta_{t-1} + \epsilon_t^\zeta, \ \epsilon_t^\zeta \sim iid(0, \sigma_\zeta). \tag{B.30}$$

News shocks are defined here using a smooth news process by introducing stochastic drift terms (z_t^A for TFP and z_t^S for IST) whose persistence parameters ($\rho_{z,A}$ and $\rho_{z,S}$) determine the smoothness of the news shocks' effects on their corresponding fundamental (see, e.g., Leeper and Walker

(2011), Leeper et al. (2013), and Barsky and Sims (2011, 2012)). Note that the stochastic pocesses for TFP and IST are defined here in accordance with the general formulation from Equations (2) and (3) with the anticipation horizon set to $j = 1$ and the smoothness parameters ($\rho_{z,A}$ and $\rho_{z,S}$ which correspond to κ in Equation (3)) set to 0.6.

B.9 Baseline Calibration

I solve the model by log-linearizing its system of equilibrium equations about the steady state values of the variables. I calibrate the steady state growth rates of TFP and IST (μ_A and μ_S) to 0.27% and 1.03%, in accordance with the average growth rates of TFP and RPI in my empirical sample where the latter calibration is based on the long-run equivalence between IST and RPI.[38] The persistence parameters of the news shocks processes ($\rho_{z,A}$ and $\rho_{z,S}$) are both set to 0.6 and the standard deviations of the TFP news shock and IST news shock ($\epsilon_t^{A,news}$ and $\epsilon_t^{S,news}$) are set to 0.007 and 0.045, respectively. The news shocks' standard deviation calibration is set such that IST news shocks have a relatively dominant role (see related discussion on Page 34).

All other parameters' calibration follows Moura (2018), taking the estimated mode posterior values for his estimated parameters and his calibration for the parameters he did not estimate. Table B.1 presents the calibration I use for the model's parameters excluding the shock processes' related parameters; these parameters are separately presented in Table B.2. This calibration underlies the Monte Carlo experiment of Section 5.1. I now turn to discussing the alterations I make to this baseline calibration for the Monte Carlo experiment of Section 5.2.

B.10 Calibration for Monte Carlo Experiment of Section 5.2

Since my objective in Section 5.2 is to produce a DSGE model based DGP with IST news shocks that comply with Restrictions 1 and 2, but also at the same time maintain a reasonable calibration in terms of data fit and previous research, I try to alter as few as possible parameters' values. That said, in weighing the tradeoff between consistency with the DSGE literature and being able to obtain a suitable DGP for the sake of the sought after Monte Carlo experiment of Section 5.2, I

[38]This implies a steady state real GDP growth rate of $\mu = \mu_A + \alpha_C \mu_S = 0.54\%$, where $\alpha_C = 0.35$ in accordance with the calibration from Moura (2018).

place a much larger weight on the former. I alter five parameters relative to the baseline calibration from Table B.1 (non-shock related parameters): I change the Calvo price rigidity parameter in the investment sector from 0.93 to 0, inverse elasticity of intertemporal substitution (σ_c) from 1.26 to 0.25, consumption habit formation (h) from 0.64 to 0, inverse Frisch elasticity (σ_l) from 1.23 to 100, and coefficient on output growth in the Taylor rule (r_y) from 0.72 to 0. Relative to the calibration of the shocks' standard deviations from Table B.2, I modify the baseline standard deviations by multiplying by 25% all of them but that of the IST news shock, which I calibrate to 0.042. The changes in the parameters from Table B.1 generate an IST news shock that conforms to the impact comovement restriction while those in the shocks' standard deviations ensure that the IST news shock accounts for the bulk of the business cycle variation in the real aggregates and also that this shock has effects that are not overwhelmingly large (with the exception of RPI and investment responses at longer horizons; also see Footnote 33).

I shall now briefly discuss the role of each change of the parameters from Table B.1. As already discussed by Liu et al. (2012) and Moura (2018) in the context of IST surprise shocks, price rigidity in the investment sector makes IST improvements less expansionary because these leave some of investment goods prices unchanged and thus relatively expensive with respect to the future, which in turn generates a large fall in investment demand owing to households being roughly indifferent to the timing of investment purchases. This mechanism, which is naturally also relevant to anticipated improvements in IST, also puts downward pressure on investment sector hours (which are mostly demand-driven in the short run). To eliminate this mechanism, I simply remove investment sector price rigidities from the model. Since IST news shocks persistently raise real interest rates in the baseline model, lowering σ_c makes consumption growth more responsive to IST news shocks which in turn allows investment to rise more on impact for a given output level; this lowering also limits the negative wealth effect of IST news shocks on hours which in turn helps to generate an impact rise in hours. To simultaneously also increase the impact rise in consumption which is diminished by the lowering of σ_c, I remove habit formation from the model as it allows for a less smooth consumption response and thus a greater corresponding impact rise. When $\sigma_c < 1$, households FOC with respect to consumption implies complementarity between consumption and leisure whose strength is governed by the inverse Frisch elasticity of labor supply; hence, raising the latter allows for more room for hours to rise in tandem with the rise in consumption. Lastly, I remove the responsiveness of interest rates to output growth in the Taylor-like rule so as to allow for a more accommodative monetary policy in the presence of a favorable IST news shock.

Table B.1: **Model Parameterization: Non-Shock Related Parameters**.

Parameter	Description	Value
β	Subjective discount factor	0.998
δ	Depreciation rate	0.025
$\phi^{w,C}; \phi^{w,I}; \phi^{p,C}; \phi^{p,I}$	Labor and goods market elasticity of substitution	10
π^*_C	Steady state gross C inflation	1.011
μ_A	Steady state TFP gross growth rate	1.0027
μ_S	Steady state IST gross growth rate	1.013
α_C, α_I	Capital share	0.35;0.35
$\frac{G^C}{Y^C}$	Steady state government consumption share	0.23
$\frac{G^I}{Y^I}$	Steady state government investment share	0.15
σ_c	Inverse elasticity of inter-temporal substitution	1.26
h	Habit formation parameter	0.64
σ_l	Inverse Frisch elasticity	1.23
$\xi_{p,C}; \xi_{p,I}$	Degree of nominal rigidities in the goods market	0.78;0.93
$\xi_{w,C}; \xi_{w,I}$	Degree of nominal rigidities in the labor market	0.85;0.98
$\iota_{p,C}; \iota_{p,I}$	Degree of price indexation to past inflation	0.18;0.13
$\iota_{w,C}; \iota_{w,I}$	Degree of wage indexation to past inflation	0.11;0.18
ω	Capital utilization elasticity	0.94
ϖ	Steady-state elasticity of the investment adjustment cost function	3.97
τ	Reallocation cost: Labor	2.77
ν	Reallocation cost: Capital	0.12
r_π	Coefficient on inflation in the interest rate rule	1.91
r_y	Coefficient on output growth in the interest rate rule	0.72
ρ_R	Degree of interest rate smoothing	0.77

Notes: The table consists of the non-shock parameters values used for the model described in Appendix B. This calibration underlies the Monte Carlo experiment of Section 5.1. The third column shows the values for both the consumption and investment sectors, whenever such a distinction applies.

Table B.2: **Model Parameterization: Shock Related Parameters**.

Parameter	Description	Value
$\rho_{z,A}$	TFP news shock persistence	0.6
$\rho_{z,S}$	IST news shock persistence	0.6
$\rho_{G,C}$	Government consumption shock persistence	0.97
$\rho_{G,I}$	Government investment shock persistence	0.96
ρ_{ζ}	Preference shock persistence	0.93
$\sigma_{A,surprise}$	TFP surprise shock standard deviation	0.00902
$\sigma_{S,surprise}$	IST surprise shock standard deviation	0.0202
$\sigma_{A,news}$	TFP news shock standard deviation	0.007
$\sigma_{S,news}$	IST news shock standard deviation	0.045
σ_{R}	Monetary policy shock standard deviation	0.00253
$\sigma_{G,C}$	Government consumption shock standard deviation	0.0125
$\sigma_{G,I}$	Government investment shock standard deviation	0.0262
σ_{ζ}	Preference shock standard deviation	0.0219

Notes: The table consists of the shock parameters values used for the model described in Appendix B. This calibration underlies the Monte Carlo experiment of Section 5.1.

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Table 1: **Long-Run Implications of Business Cycle Shock for RPI and TFP.**

	Impulse Response	Forecast Error Variance Contribution
Baseline VAR: RPI	-2.4% [-5.2%,-1.5%]	80% [61%,88%]
Baseline VAR: TFP	1% [0.5%,2.4%]	54% [21%,78%]
Post-1982 VAR: RPI	-2.2% [-5.1%,-1.3%]	81% [67%,88%]
Post-1982 VAR: TFP	0.8% [0.3%,2%]	54% [17%,78%]
VAR With Stock Prices: RPI	-2.7% [-6.3%,-1.7%]	81% [66%,88%]
VAR With Stock Prices: TFP	1.2% [0.6%,3.2%]	57% [32%,77%]
1959-2007 Sample: RPI	-2.6% [-5.9%,-1.6%]	81% [64%,88%]
1959-2007 Sample: TFP	0.9% [0.4%,2.4%]	51% [19%,78%]
Shadow Rate: RPI	-2.8% [-6.2%,-1.6%]	80% [60%,88%]
Shadow Rate: TFP	1.2% [0.5%,3.3%]	59% [27%,79%]
10-Year Treasury Rate: RPI	-2.7% [-6.3%,-1.7%]	81% [66%,88%]
10-Year Treasury Rate: TFP	1.2% [0.6%,3.2%]	57% [32%,77%]
Imposing Cointegration: RPI	-2.4% [-4.5%,-1.5%]	76% [56%,87%]
Imposing Cointegration: TFP	1% [0.4%,2.2%]	47% [18%,73%]
Investment TFP: RPI	2.7% [1.6%,5.6%]	78% [54%,87%]
Investment TFP: TFP	1.2% [0.6%,2.9%]	64% [35%,82%]
Alternative Inflation Measure: RPI	-2.5% [-5%,-1.5%]	81% [62%,88%]
Alternative Inflation Measure: TFP	1.1% [0.5%,2.6%]	57% [32%,77%]

Notes: This table presents the median and 16th and 84th percentiles of the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock in the baseline model as well as alternative model specifications (see Section 4). The 16th and 84th percentiles appear in squared brackets next to the median estimate.

Table 2: **Mean Realization of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock in Boom-Bust Period.**

	Business Cycle Shock	Other Long-Run Shock
Baseline VAR: Boom Period Mean Realization	0.49 [0.34,0.65]	0.04 [-0.22,0.31]
Baseline VAR: Bust Period Mean Realization	-0.33 [-0.57,-0.18]	-0.06 [-0.35,0.27]
Post-1982 VAR: Boom Period Mean Realization	0.38 [0.18,0.58]	-0.02 [-0.29,0.25]
Post-1982 VAR: Bust Period Mean Realization	-0.35 [-0.57,-0.12]	0.06 [-0.33,0.45]
VAR With Stock Prices: Boom Period Mean Realization	0.38 [0.21,0.57]	-0.04 [-0.31,0.23]
VAR With Stock Prices: Bust Period Mean Realization	-0.37 [-0.59,-0.17]	-0.01 [-0.45,0.37]
1959-2007 Sample: Boom Period Mean Realization	0.52 [0.35,0.70]	0.01 [-0.25,0.23]
1959-2007 Sample: Bust Period Mean Realization	-0.39 [-0.56,-0.20]	-0.05 [-0.38,0.24]
Shadow Rate: Boom Period Mean Realization	0.43 [0.27,0.59]	0.08 [-0.18,0.31]
Shadow Rate: Bust Period Mean Realization	-0.42 [-0.61,-0.24]	-0.01 [-0.35,0.26]
10-Year Treasury Rate: Boom Period Mean Realization	0.38 [0.21,0.57]	0.04 [-0.31,0.23]
10-Year Treasury Rate: Bust Period Mean Realization	-0.37 [-0.59,-0.17]	-0.01 [-0.45,0.37]
Imposing Cointegration: Boom Period Mean Realization	0.49 [0.33,0.65]	-0.08 [-0.29,0.18]
Imposing Cointegration: Bust Period Mean Realization	-0.33 [-0.53,-0.11]	0.11 [-0.35,0.46]
Investment TFP: Boom Period Mean Realization	0.47 [0.31,0.63]	-0.01 [-0.26,0.27]
Investment TFP: Bust Period Mean Realization	-0.43 [-0.60,-0.25]	0.08 [-0.26,0.38]
Alternative Inflation Measure: Boom Period Mean Realization	0.50 [0.33,0.66]	0.06 [-0.22,0.32]
Alternative Inflation Measure: Bust Period Mean Realization	-0.36 [-0.55,-0.19]	-0.04 [-0.37,0.28]

Notes: This table presents the median and 16th and 84th percentiles of the mean realization of the business cycle shock and the other shock driving long-run RPI variation in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods. Results for the baseline VAR, as well as alternative model specifications (see Section 4), are shown. For the baseline VAR, in 1233 models out of the set of 1297 admissible models the business cycle shock is also one the two IST shocks, i.e., the shocks driving long-run RPI variation. To avoid inclusion of non-IST shocks that nonetheless, when coupled with the business cycle shock, drive more than 90% of long-run RPI variation, I only consider for the other long-run RPI shock models where this shock drives at least 5% of the long-run RPI variation, leaving me with 982 such models. Hence, the results on the other long-run RPI shock are based on these 982 models, or 76% of the total number of admissible models (a roughly similar share applies to the other model specifications).

Table 3: **Contribution of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock to Investment Boom-Bust Episode.**

	Business Cycle Shock	Other Long-Run Shock
Baseline VAR: Boom Period Contribution	97% [62%,131%]	7% [-13%,37%]
Baseline VAR: Bust Period Contribution	161% [94%,226%]	1% [-38%,39%]
Post-1982 VAR: Boom Period Contribution	88% [32%,144%]	20% [-14%,69%]
Post-1982 VAR: Bust Period Contribution	138% [62%,213%]	5% [-60%,60%]
VAR With Stock Prices: Boom Period Contribution	84% [47%,121%]	10% [-10%,47%]
VAR With Stock Prices: Bust Period Contribution	169% [96%,241%]	11% [-39%,53%]
1959-2007 Sample: Boom Period Contribution	93% [55%,131%]	1% [-25%,23%]
1959-2007 Sample: Bust Period Contribution	120% [61%,184%]	-5% [-38%,24%]
Shadow Rate: Boom Period Contribution	83% [48%,116%]	10% [-12%,41%]
Shadow Rate: Bust Period Contribution	175% [112%,237%]	2% [-37%,41%]
10-Year Treasury Rate: Boom Period Contribution	84% [47%,121%]	10% [-10%,47%]
10-Year Treasury Rate: Bust Period Contribution	169% [96%,241%]	11% [-39%,53%]
Imposing Cointegration: Boom Period Contribution	54% [26%,84%]	8% [-9%,31%]
Imposing Cointegration: Bust Period Contribution	140% [85%,194%]	-5% [-43%,31%]
Investment TFP: Boom Period Contribution	88% [52%,124%]	5% [-17%,32%]
Investment TFP: Bust Period Contribution	163% [101%,223%]	3% [-32%,41%]
Alternative Inflation Measure: Boom Period Contribution	97% [63%,136%]	10% [-12%,42%]
Alternative Inflation Measure: Bust Period Contribution	165% [101%,232%]	-3% [-45%,42%]

Notes: This table presents the median and 16th and 84th percentiles of the contribution (in %) of the business cycle shock and the other long-run RPI shock to the change in investment in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods. Results for the baseline VAR, as well as alternative model specifications (see Section 4), are shown. The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ investment\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rates are the average growth rates for the sample periods underlying the specifications' estimation (apart for the post-1982, 1959-2007, and shadow rate specifications, all specifications are based on the baseline 1959:Q1-2017:Q3 sample). Note that a relative contribution of 100% implies that all of the gain or loss in investment is accounted for by the shock.

Table 4: **Historical Contribution of Business Cycle Shock to Real Aggregates' Per Capita Loss in U.S. Recessions (In %).**

	Output		Investment		Consumption		Hours	
Recession	Data	Contribution	Data	Contribution	Data	Contribution	Data	Contribution
1960:2-1961:1	-2.6	-2.6 [-3.3,-1.8]	-12.4	-9.4 [-12.6,-6.5]	-1.2	-1.5 [-1.9,-1.2]	-3	-2.3 [-3.2,-1.4]
1969:4-1970:4	-4	-1.8 [-3,-0.5]	-11.7	-6.4 [-10.2,-2.7]	-0.7	-0.9 [-1.7,-0.1]	-5.1	-2.2 [-3.3,-0.8]
1973:4-1975:1	-5.6	-3.9 [-5.3,-2.3]	-15.5	-12.2 [-16.5,-6.8]	-4.5	-2.6 [-3.6,-1.5]	-4.1	-4 [-5.4,-2.4]
1980:1-1980:3	-3.8	-1 [-1.7,-0.3]	-15.3	-3.7 [-5.9,-1.5]	-1.9	-0.6 [-1.1,-0.1]	-3	-1.1 [-1.7,-0.6]
1981:3-1982:4	-6.1	-1.2 [-3,0.7]	-20.8	-3.7 [-10.3,2.8]	-0.4	-0.8 [-1.8,0.3]	-4.7	-0.2 [-2.4,2.1]
1990:3-1991:1	-2.6	-1.5 [-2.1,-1]	-9.8	-6 [-7.8,-4.2]	-1.7	-0.9 [-1.3,-0.6]	-1.9	-1.6 [-2,-1.1]
2001:1-2001:4	-1.7	-1.2 [-1.9,-0.4]	-4.8	-5.5 [-8.3,-3]	-1	-0.4 [-0.9,0.1]	-4.2	-2.1 [-2.8,-1.4]
2007:4-2009:2	-7.9	-5.5 [-7.3,-3.9]	-34	-18.7 [-25.2,-12.8]	-4.8	-3.4 [-4.6,-3.3]	-10.2	-5.8 [-7.8,-3.8]

Notes: This table presents the estimates of the contribution of the business cycle shock to each of the recessions in my sample period. The first column ('Data') for each variable presents the percentage change from peak to trough of the corresponding real aggregate per capita, relative to trend growth, in every recession. The second column reports the median contribution of the business cycle shock to the corresponding real aggregate's loss with the numbers in squared brackets below it representing the 16th and 84th posterior percentiles of the contribution. Trend growth rates are computed from the average growth rates of each real aggregate per capita over the sample.

Table 5: **Low-Frequency Correlation of Hours Worked in Levels and Differences with RPI and TFP Growth Rates.**

	HP-Trend of RPI Growth	HP-Trend of TFP Growth
HP-Trend of Hours Worked	74%	52%
HP-Trend of Hours Worked Growth	-8%	-4%

Notes: This table presents the correlations (in %) of the HP-trends of hours worked in logs and log-first-differences with the HP-trends of the log-first-differences of RPI and TFP.

Table 6: **Lifting the Long-Run Restriction: Long-Run Implications of Business Cycle Shock for RPI and TFP.**

	Impulse Response	Forecast Error Variance Contribution
Baseline VAR: RPI	-1.5% [-3.2%,-0.7%]	44% [12%,69%]
Baseline VAR: TFP	0.8% [0.3%,1.7%]	38% [11%,65%]

Notes: This table presents the median and 16th and 84th percentiles of the long-run impulse response and FEV share of RPI and TFP due to the business cycle shock from an estimation that only imposes set of restrictions 1 (excluding the long-run restriction 2). The 16th and 84th percentiles appear in squared brackets next to the median estimate.

Table 7: **Lifting the Long-Run Restriction: Mean Realization of Business Cycle Shock and Contribution to Investment Variation in Boom-Bust Period.**

	Mean Realization	Contribution to Investment Variation
Baseline VAR: Boom Period	0.51 [0.38,0.64]	85% [53%,120%]
Baseline VAR: Bust Period	-0.35 [-0.54,-0.17]	166% [102%,229%]
Levels VAR: Boom Period	0.51 [0.30,0.72]	68% [30%,105%]
Levels VAR: Bust Period	-0.25 [-0.45,-0.05]	120% [69%,171%]

Notes: This table presents the median and 16th and 84th percentiles of the mean realization of the business cycle shock and the contribution (in %) of this shock to the change in investment in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods from an estimation that only imposes set of restrictions 1 (excluding the long-run restriction 2). The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ investment\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for investment is assumed to be 2.8%, which is the average growth rate for the sample period. Note that a relative contribution of 100% implies that all of the gain or loss in investment is accounted for by the shock. While the first two rows correspond to the estimation of the baseline (stationary) VAR, the next two rows show the results from estimating a levels VAR for which the long-run restriction is meaningless and is therefore also not imposed upon in estimation.

Table 8: **F-Test and R^2 of Regression of Business Cycle Shock Series on Lagged Principal Components.**

	Principal Components (from 1 to n)							
	1	2	3	4	5	6	7	8
P-Value	0.83	0.12	0.13	0.06	0.09	0.07	0.12	0.12
R^2	0	0.05	0.06	0.09	0.10	0.12	0.13	0.14

Notes: Column n reports the p-value of the F-test as well as the R^2 of the regression of the median business cycle shock series on three lags of the first n principle components extracted from the FRED-QD comprehensive quarterly data set, where n goes from 1 to 8.

Table 9: **Contribution of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock to Stock Prices Boom-Bust Episode.**

	Business Cycle Shock	Other Long-Run Shock
VAR With Stock Prices: Boom Period Contribution	62% [28%,103%]	13% [-8%,50%]
VAR With Stock Prices: Bust Period Contribution	30% [5%,59%]	6% [-8%,27%]

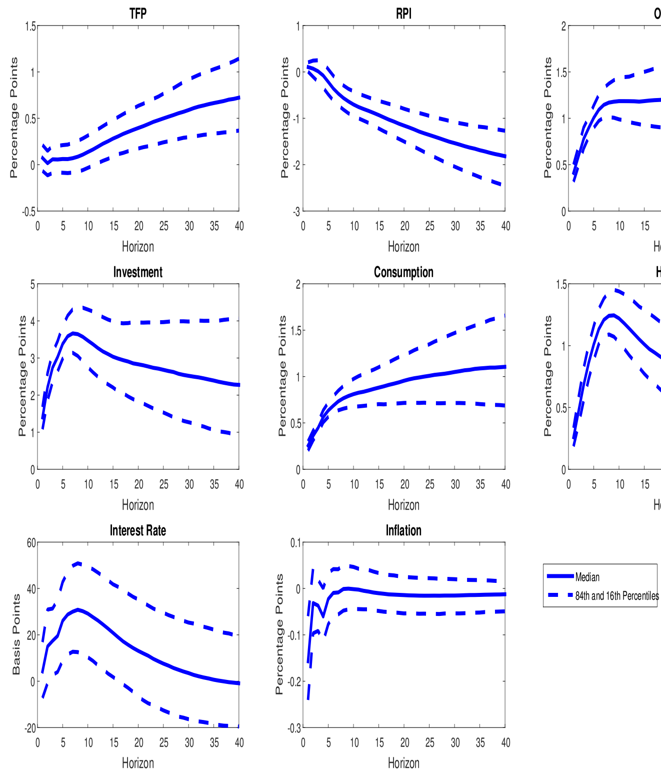
Notes: This table presents the median and 16th and 84th percentiles of the contribution (in %) of the business cycle shock and the other long-run RPI shock to the change in stock prices in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods from a VAR that includes stock prices. The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ stock\ prices\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for stock prices is assumed to be 2.8%, which is the average growth rate in the sample period. Note that a relative contribution of 100% implies that all of the gain or loss in stock prices is accounted for by the shock.

Table 10: **DSGE Model Based Monte Carlo Experiments.**

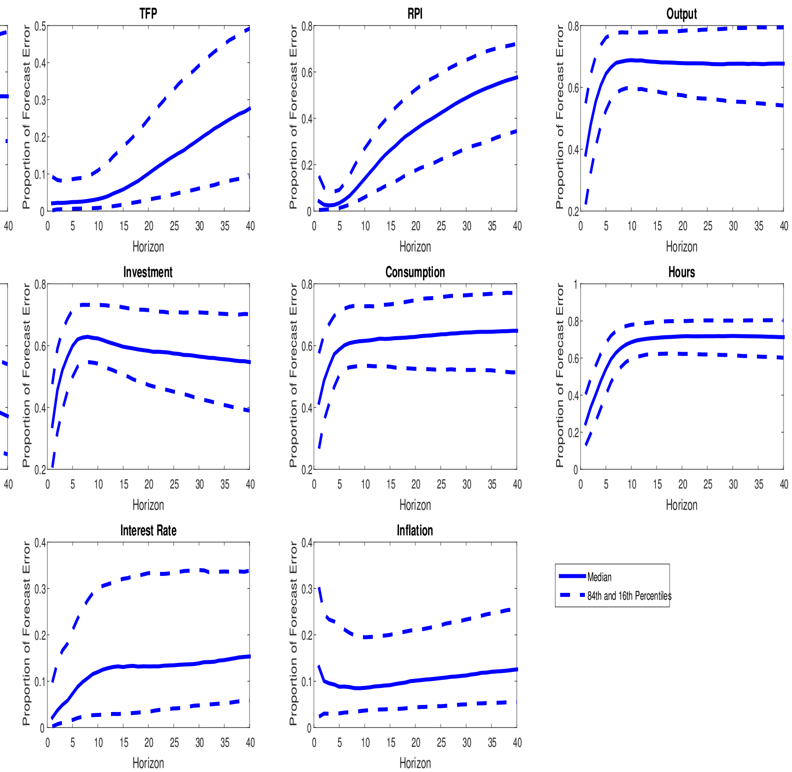
	Null Identification	Admissibility Rate
Baseline Calibration: With Long-Run RPI Restriction	96%	1.75×10^{-5}
Baseline Calibration: Without Long-Run RPI Restriction	85%	2.7×10^{-5}
Alternative Calibration: With Long-Run RPI Restriction	0%	78.2×10^{-5}
Alternative Calibration: Without Long-Run RPI Restriction	0%	1688×10^{-5}

Notes: This table presents the share of simulations in which identification was null (first column) along with the average admissibility rate (average number of admissible models divided by total number of posterior draws (10^5)) for the simulations that did produce a non-null set of admissible models (second column). A total of 100 simulations were conducted (corresponding to 100 artificial data sets from the DSGE model described in Appendix B) with the first row of the table providing results from applying my baseline identification procedure to each data set using the baseline calibration; the second row providing results from applying the baseline procedure but without imposing the long-run RPI restriction (Restriction 1) while using the baseline calibration; the third row corresponding to results from applying the baseline estimation procedure to each data set using the alterative calibration described in Section B.10; and the fourth row corresponding to results from applying the baseline procedure but without imposing the long-run RPI restriction (Restriction 1) while using the alternative calibration described in Section B.10.

Figure 1: **Baseline VAR: (a) Impulse Responses; (b) Contribution to FEV.**



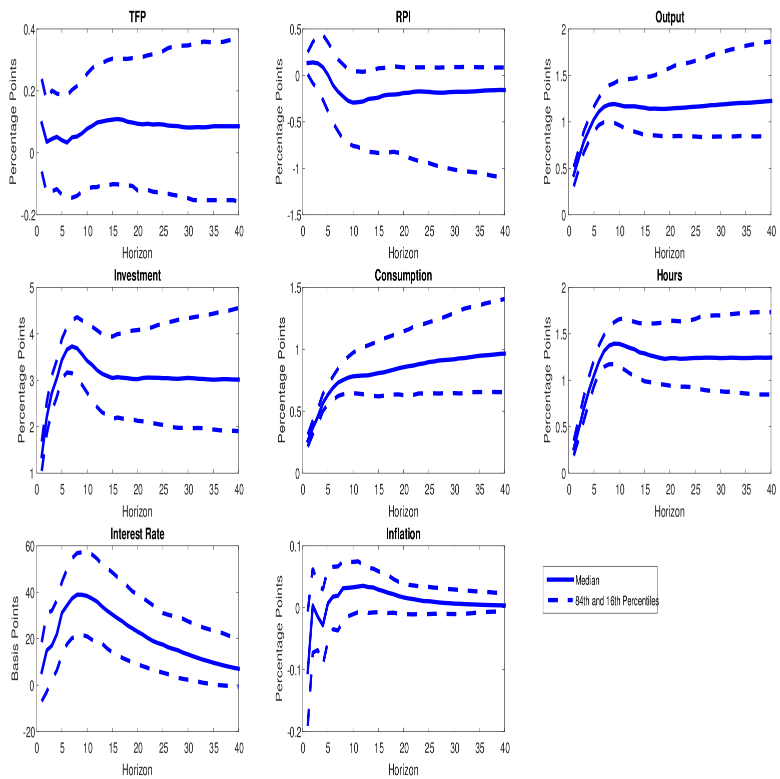
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



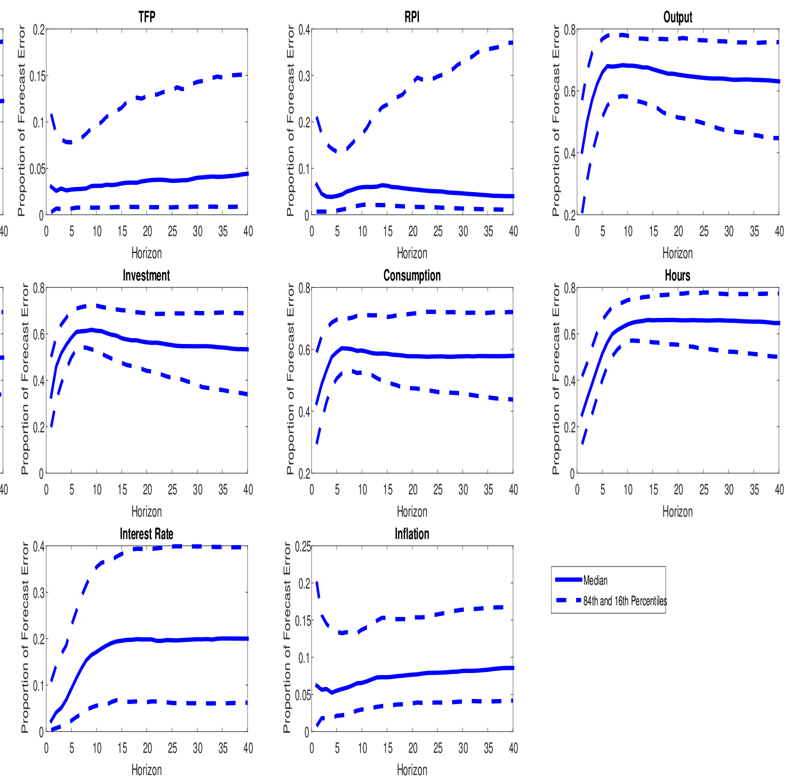
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions.

Figure 2: **Differenced Hours VAR: (a) Impulse Responses; (b) Contribution to FEV.**



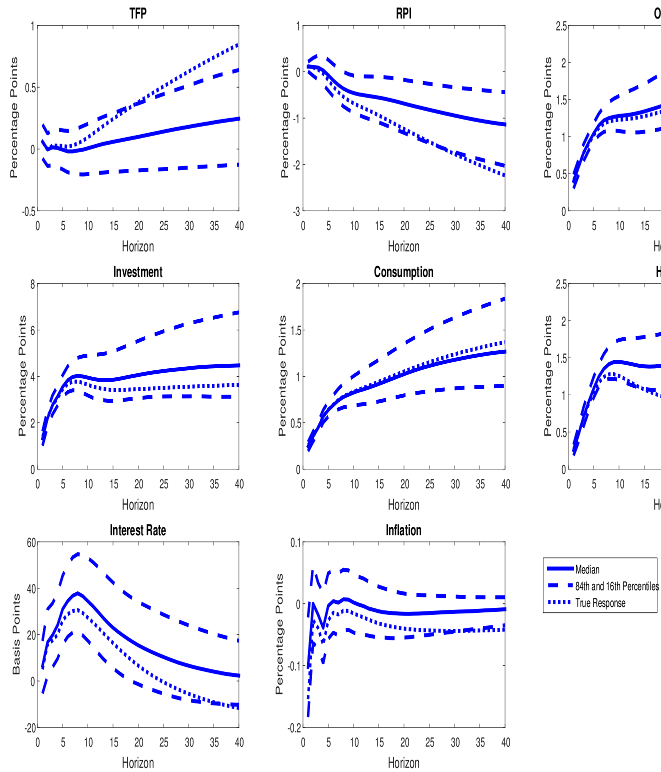
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



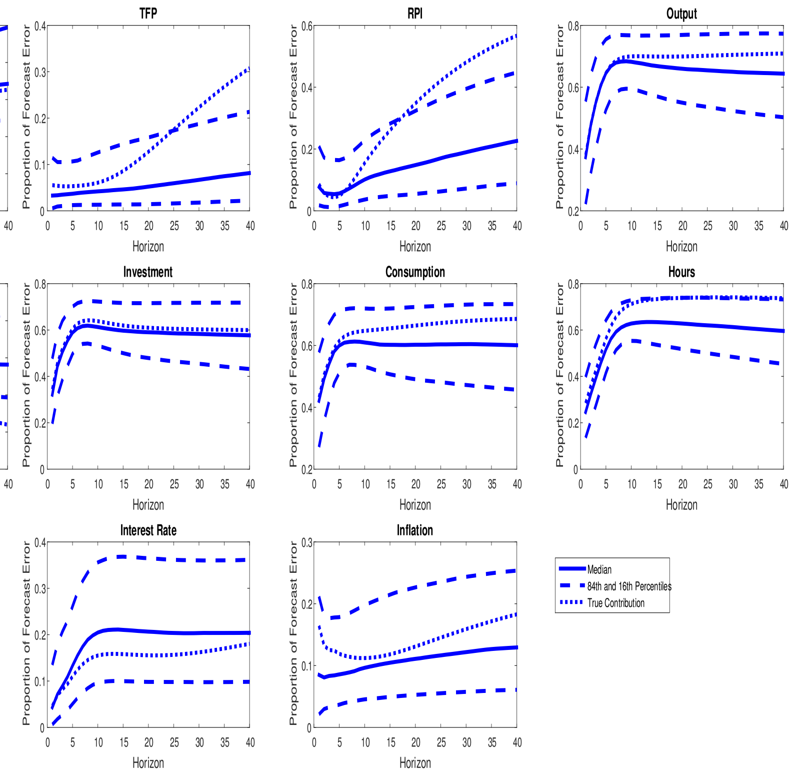
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a VAR where hours worked are specified in log-first-differences rather than in log-levels. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a VAR where hours worked are specified in log-first-differences rather than in log-levels.

Figure 3: **Monte Carlo Evidence from a Non-Stationary Hours Specification: (a) Impulse Responses; (b) Contribution to FEV.**



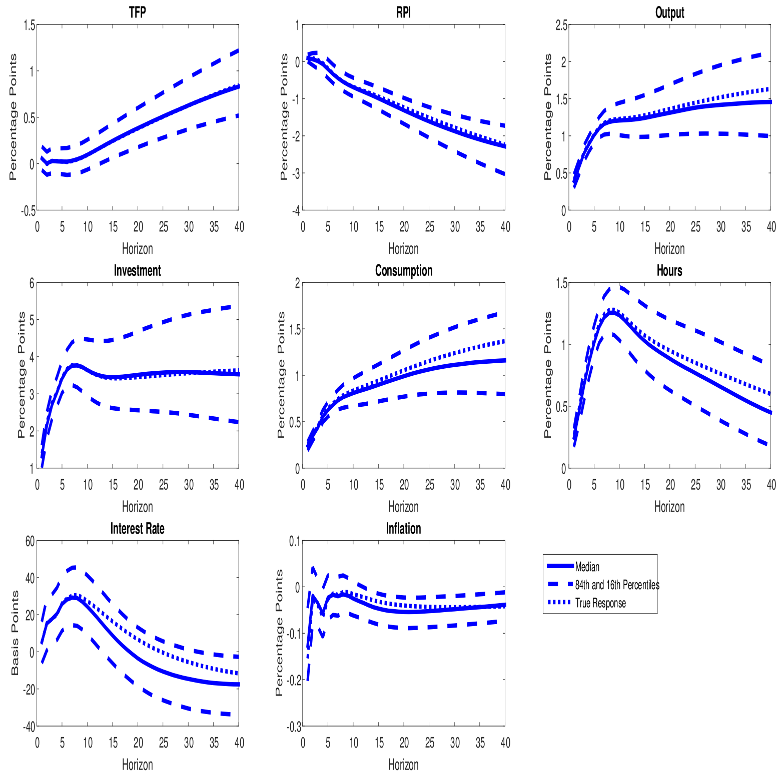
(a) The Mean Estimated Median and 84th and 16th percentile Impulse Responses and the Mean True Impulse Responses.



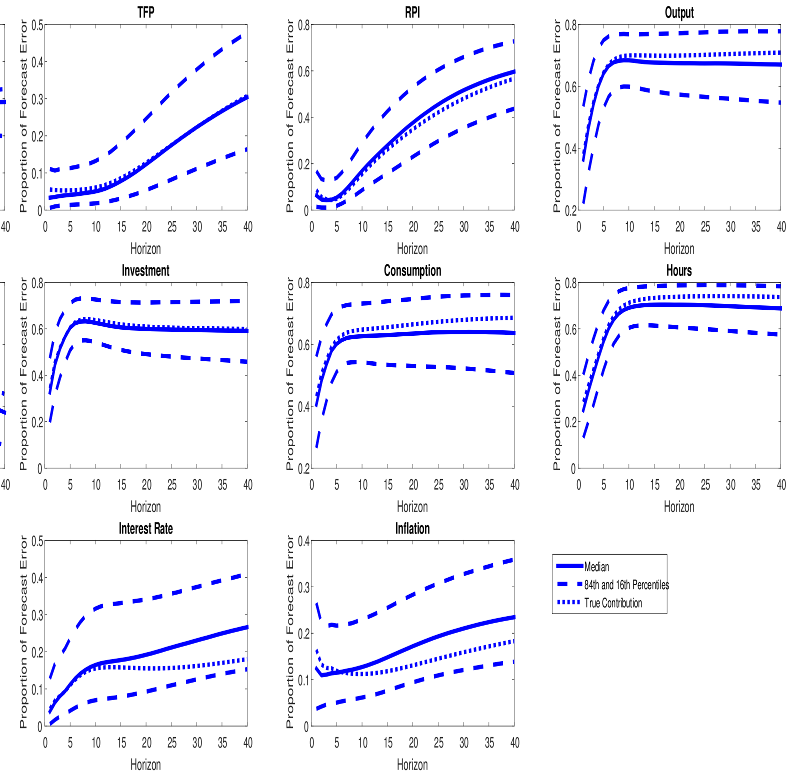
(b) The Mean Estimated Median and 84th and 16th Percentiles FEV Contributions and the Mean True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from estimating a differenced hours VAR specification with artificial data sets generated from a levels hours VAR. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true impulse response across the data generating processes. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations,the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.

Figure 4: **Monte Carlo Evidence from a Stationary Hours Specification: (a) Impulse Responses; (b) Contribution to FEV.**



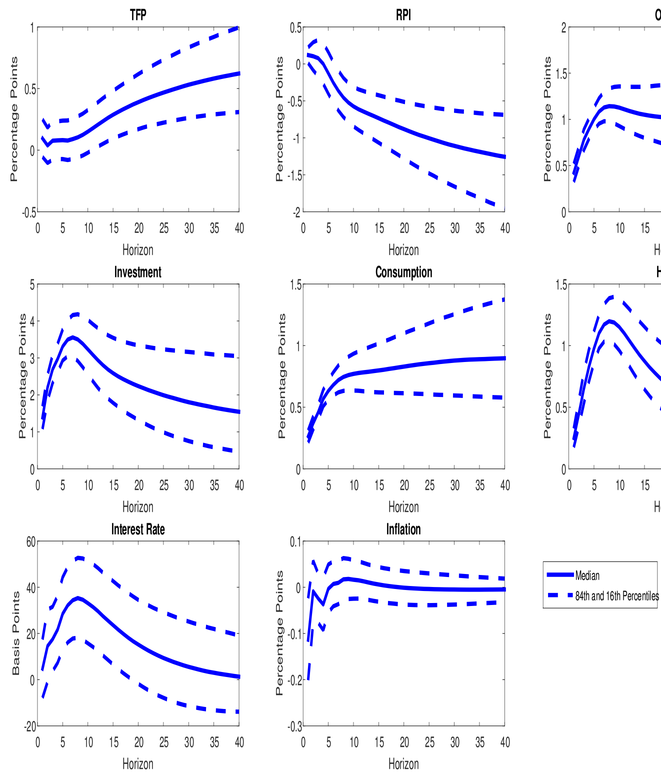
(a) The Mean Estimated Median and 84th and 16th percentile Impulse Responses and the Mean True Impulse Responses.



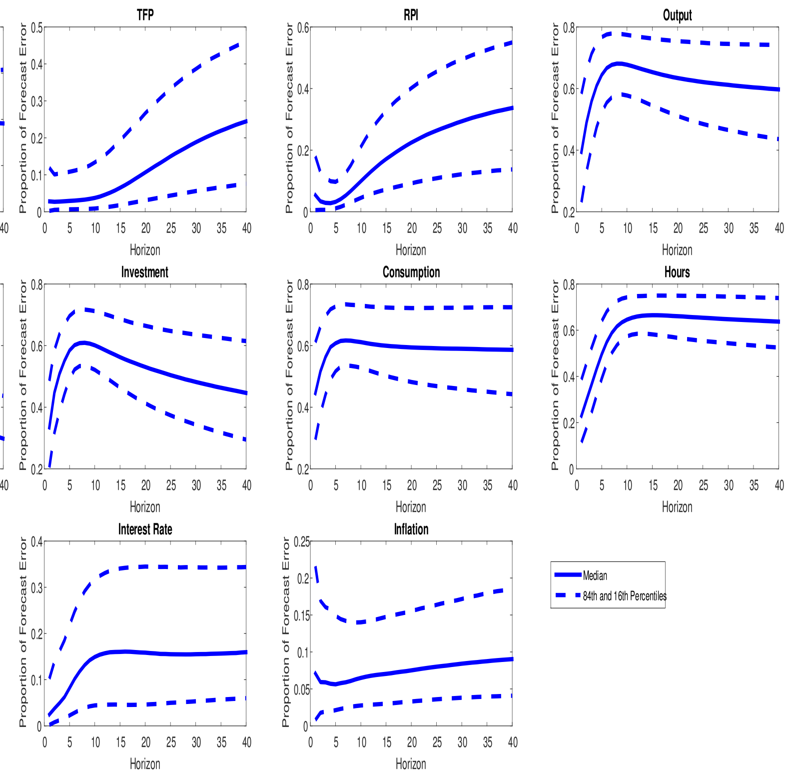
(b) The Mean Estimated Median and 84th and 16th Percentiles FEV Contributions and the Mean True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from estimating a levels hours VAR specification with artificial data sets generated from a levels hours VAR. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true impulse response across the data generating processes. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations,the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.

Figure 5: **Lifting the Long-Run Restriction: (a) Impulse Responses; (b) Contribution to FEV.**



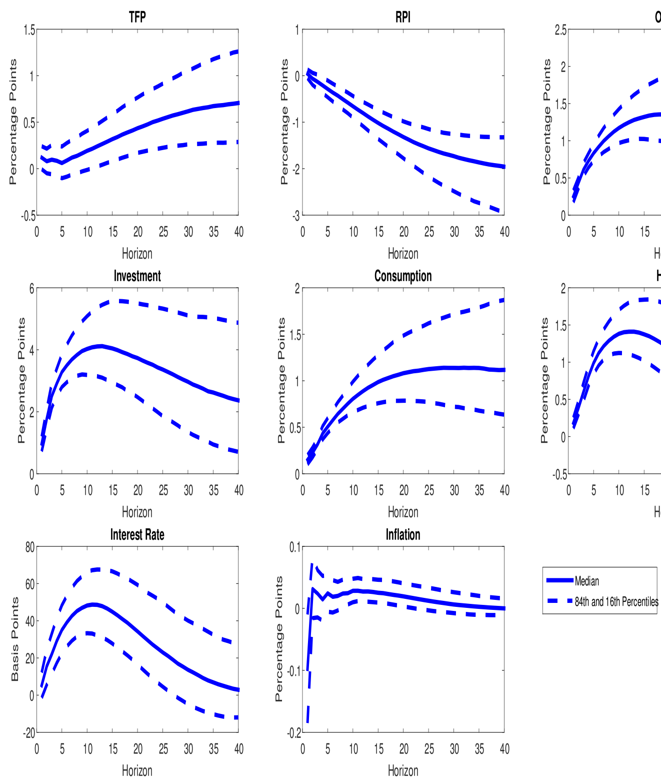
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



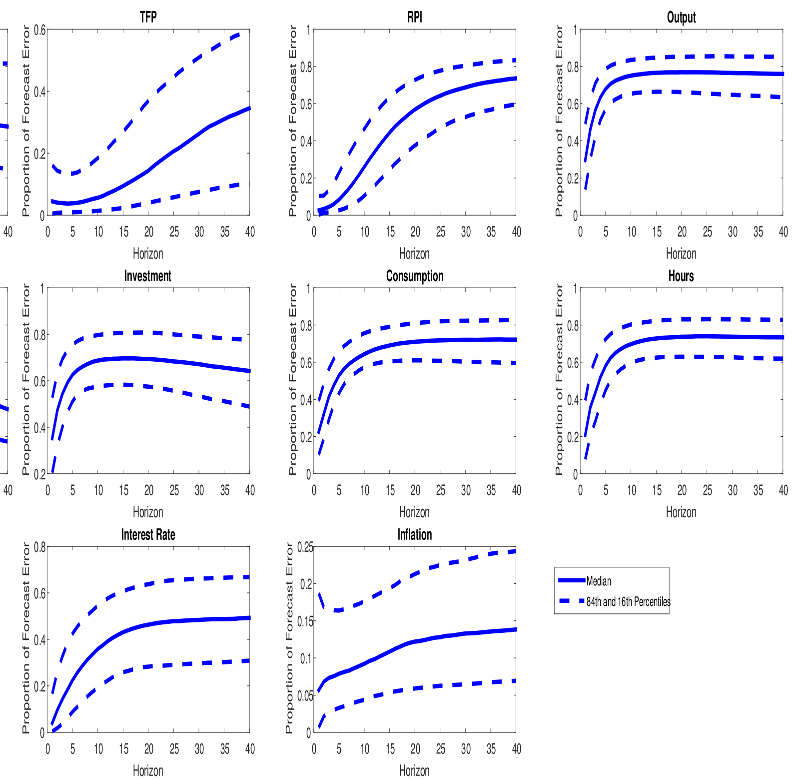
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from an estimation that does not impose the long-run restriction (Restriction 2). Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from an estimation that does not impose the long-run restriction (Restriction 2).

Figure 6: **Post-1982 VAR: (a) Impulse Responses; (b) Contribution to FEV.**



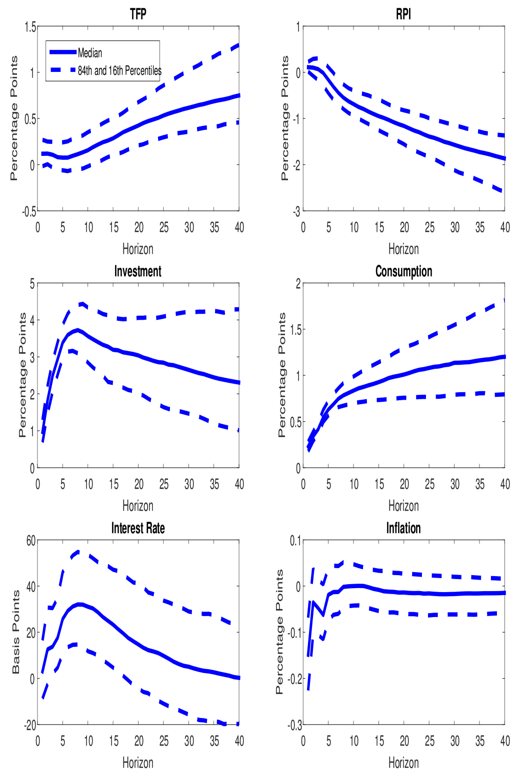
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



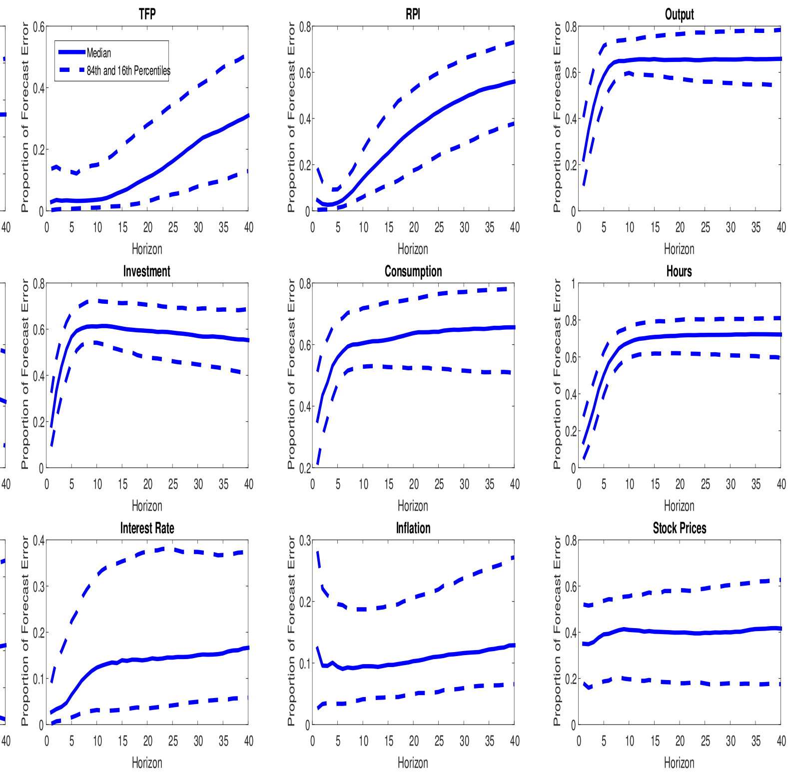
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a post-1982 VAR. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a post-1982 VAR.

Figure 7: **VAR With Stock Prices: (a) Impulse Responses; (b) Contribution to FEV.**



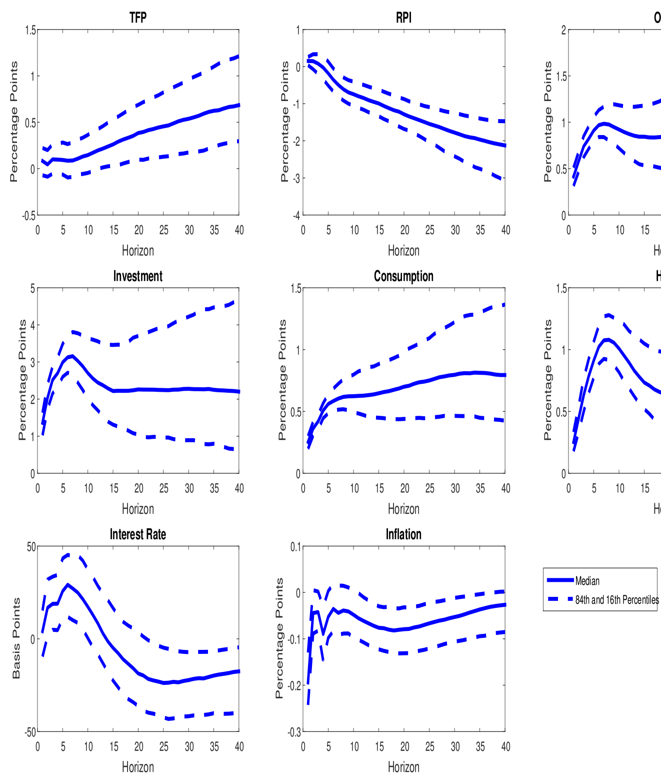
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



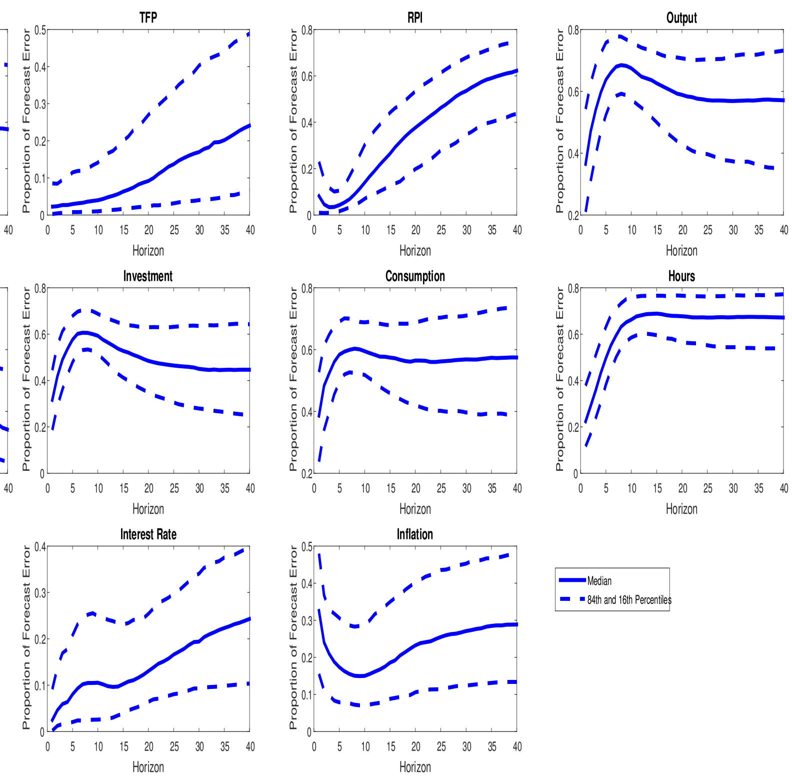
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a VAR that includes stock prices. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a VAR that includes stock prices.

Figure 8: **1959-2007 Sample: (a) Impulse Responses; (b) Contribution to FEV.**



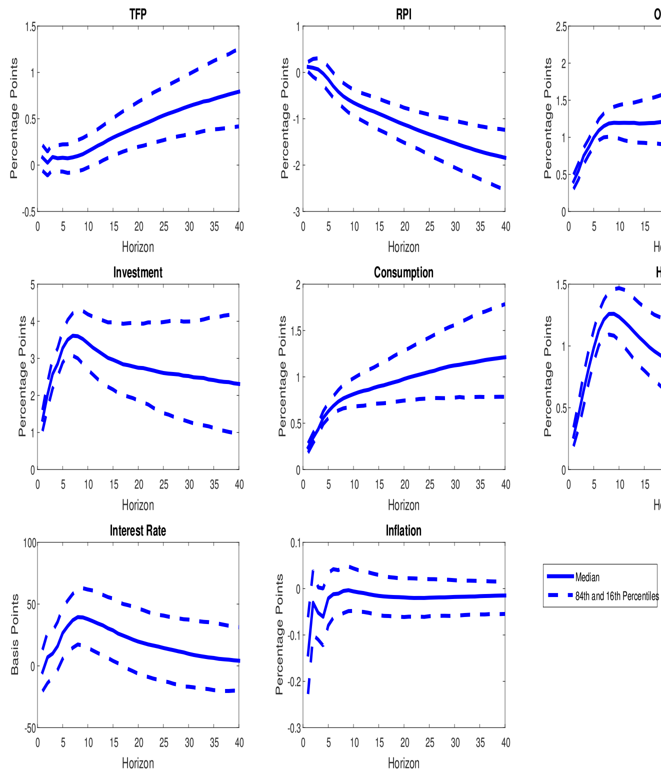
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



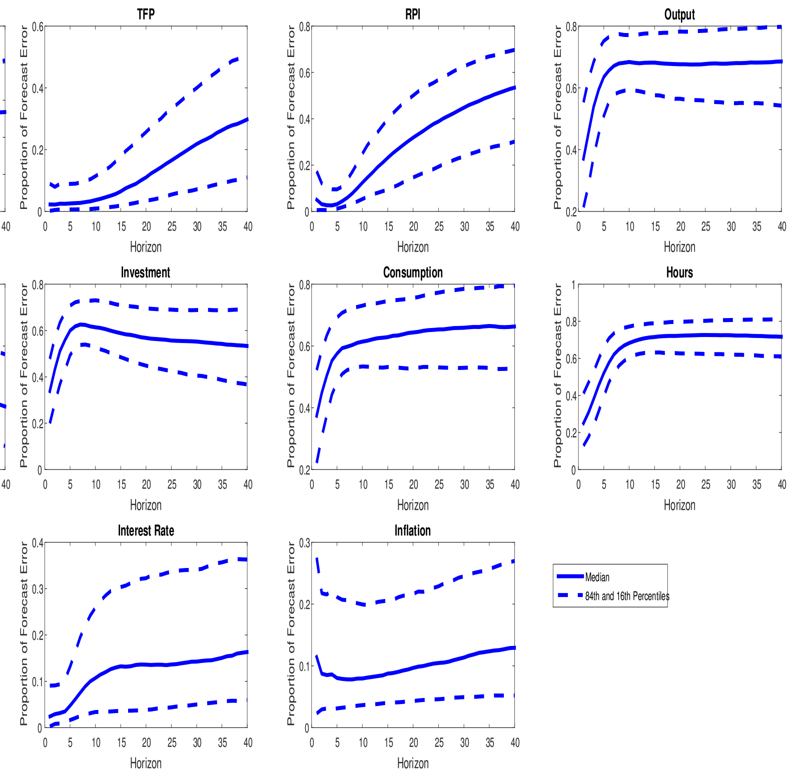
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a 1959-2007 VAR. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a 1959-2007 VAR.

Figure 9: **Shadow Rate: (a) Impulse Responses; (b) Contribution to FEV.**



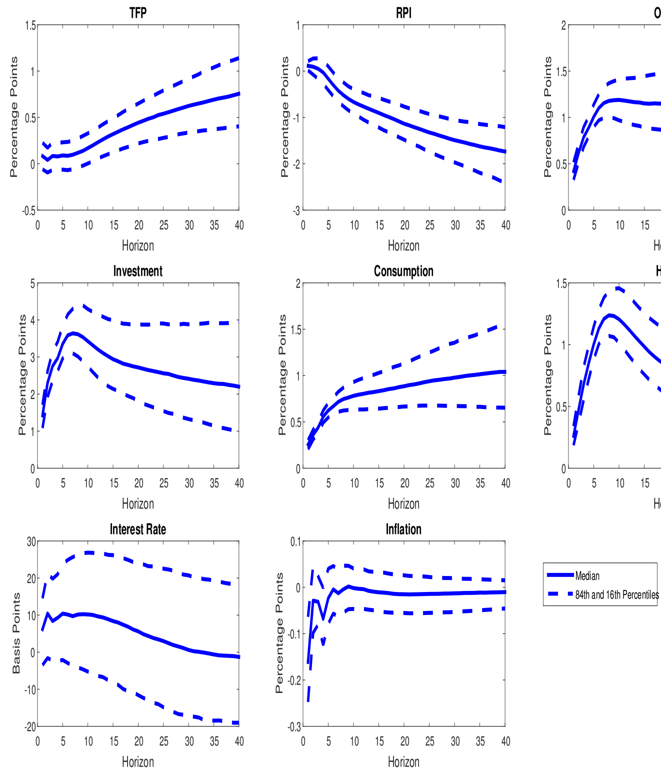
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



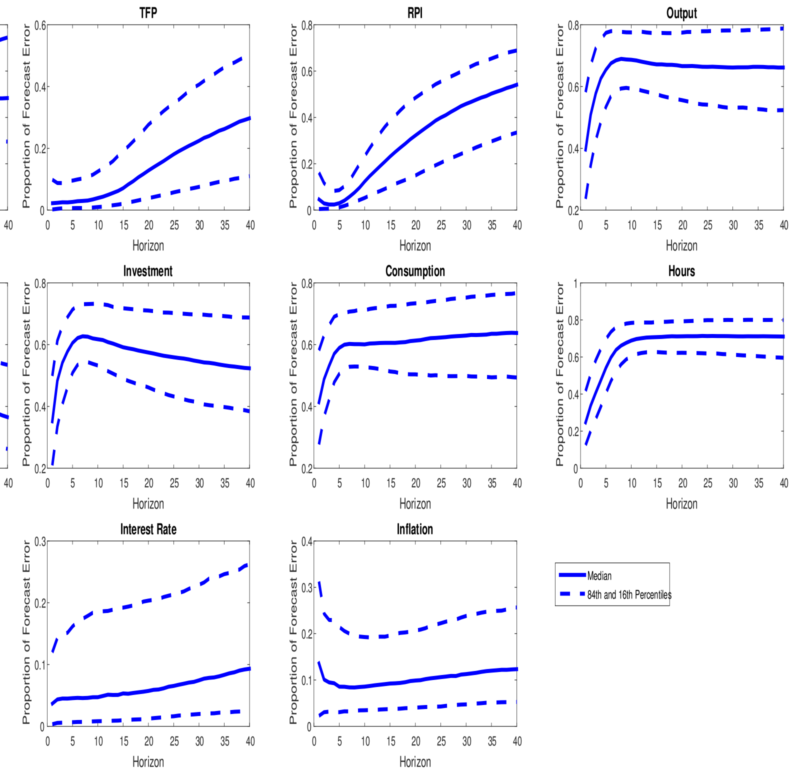
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the three month T-Bill rate with the shadow rate from WU and XIA (2016). Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the three month T-Bill rate with the shadow rate from WU and XIA (2016).

Figure 10: **10-Year Treasury Rate: (a) Impulse Responses; (b) Contribution to FEV.**



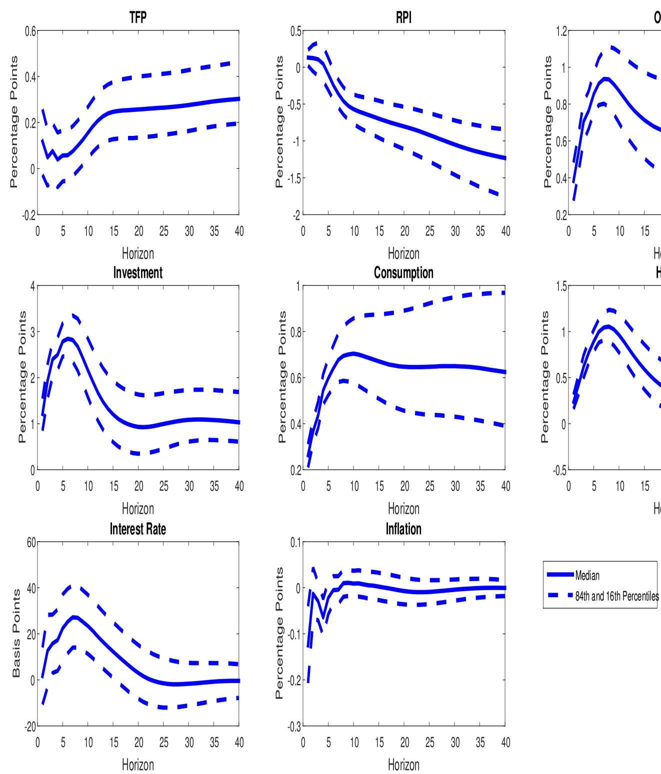
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



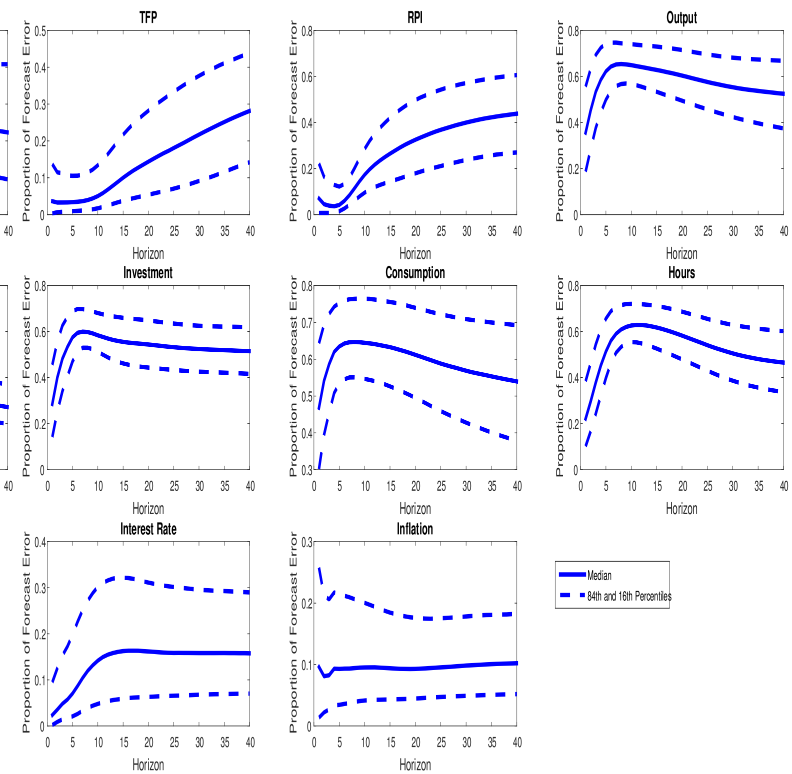
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the three month T-Bill rate with the 10-year treasury rate. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the three month T-Bill rate with the 10-year treasury rate.

Figure 11: **Levels VAR: (a) Impulse Responses; (b) Contribution to FEV.**



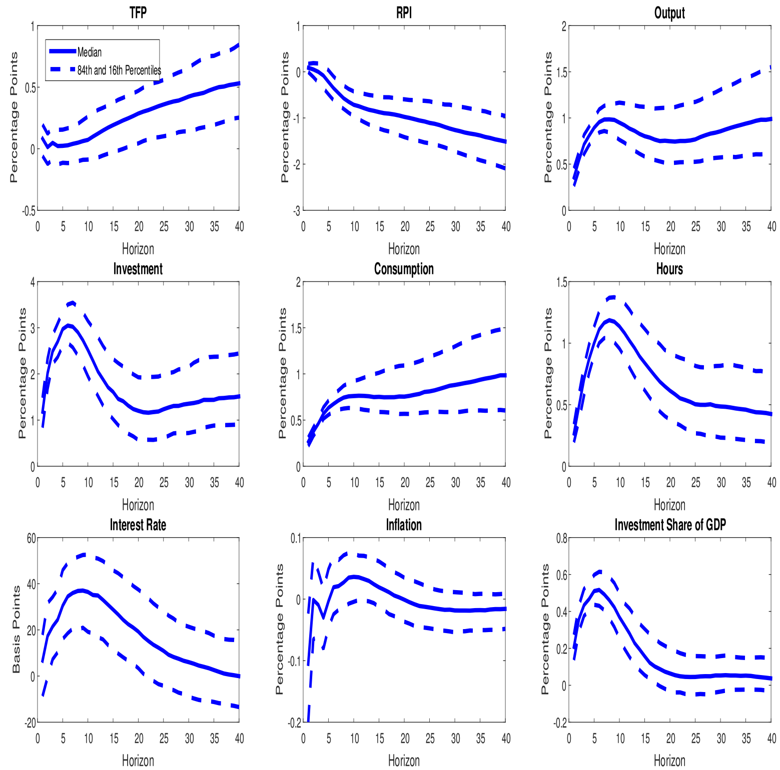
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



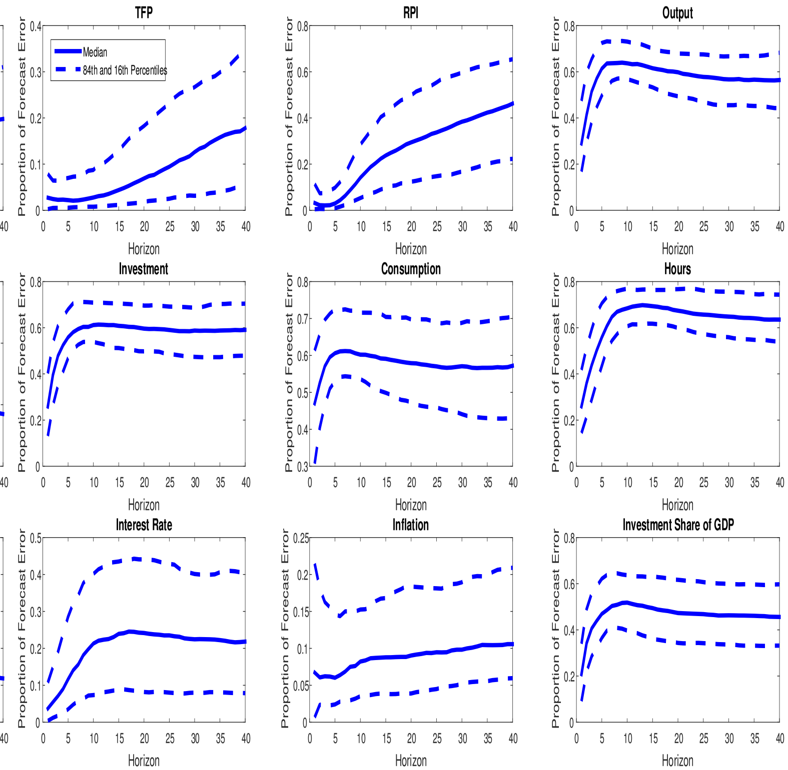
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a levels VAR. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a levels VAR.

Figure 12: **Imposing Cointegration: (a) Impulse Responses; (b) Contribution to FEV.**



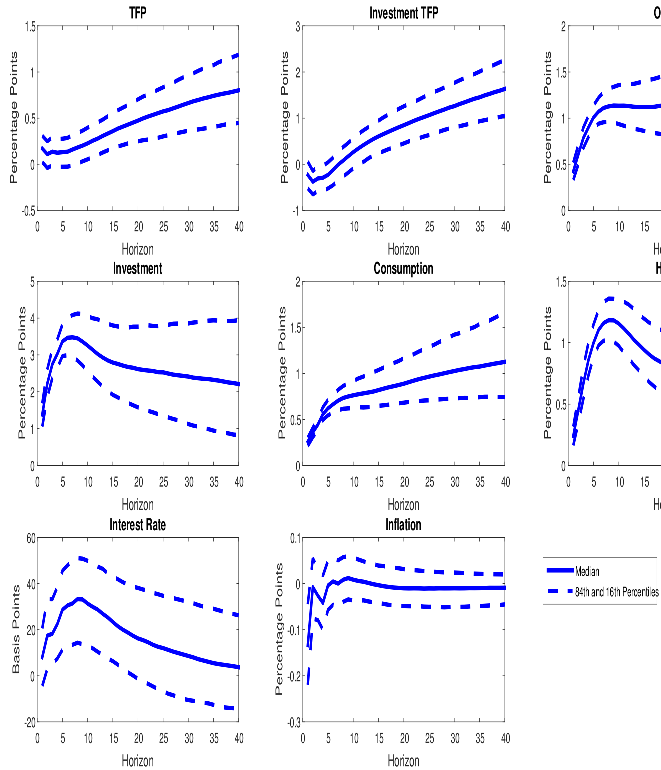
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



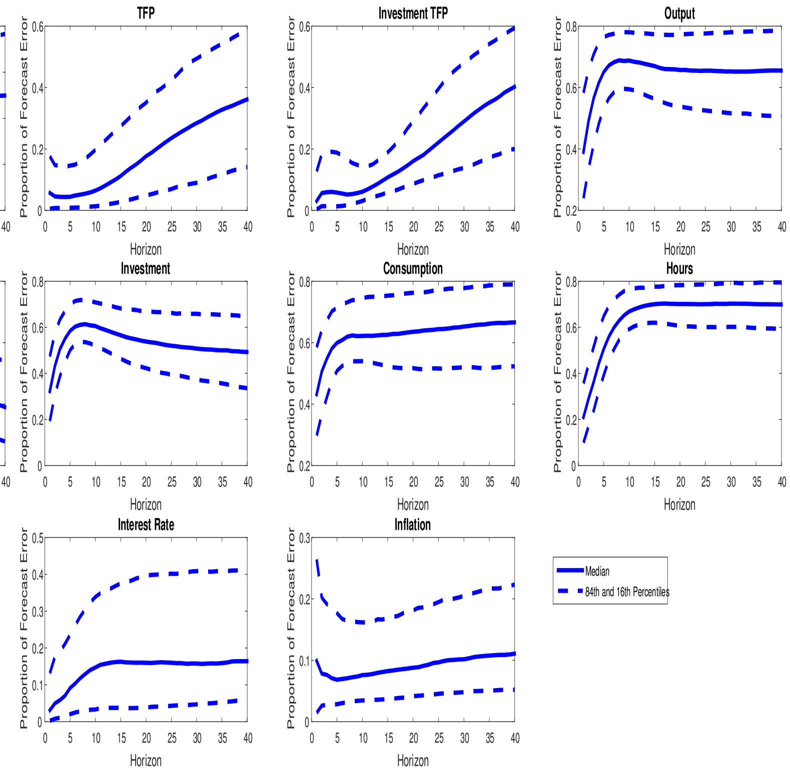
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output). Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output).

Figure 13: **Fernald (2014)'s Investment TFP: (a) Impulse Responses; (b) Contribution to FEV.**



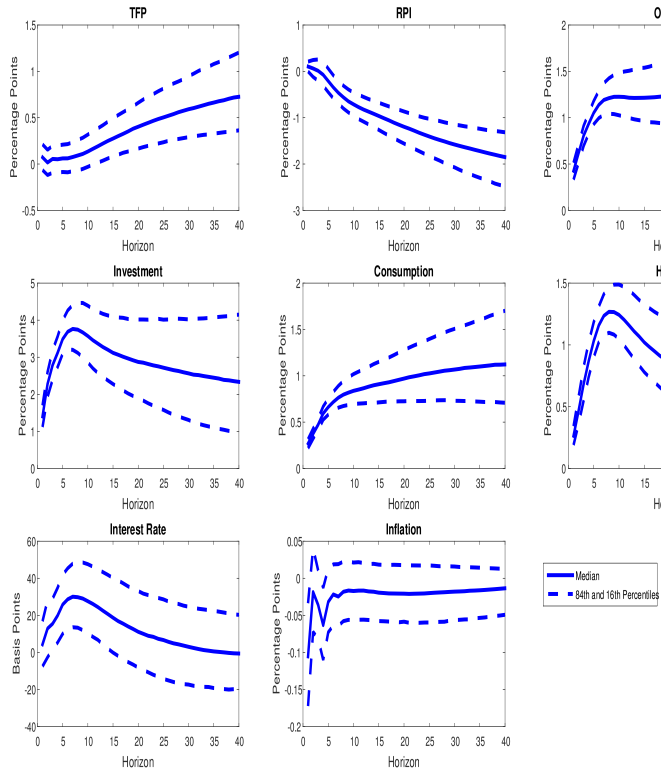
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



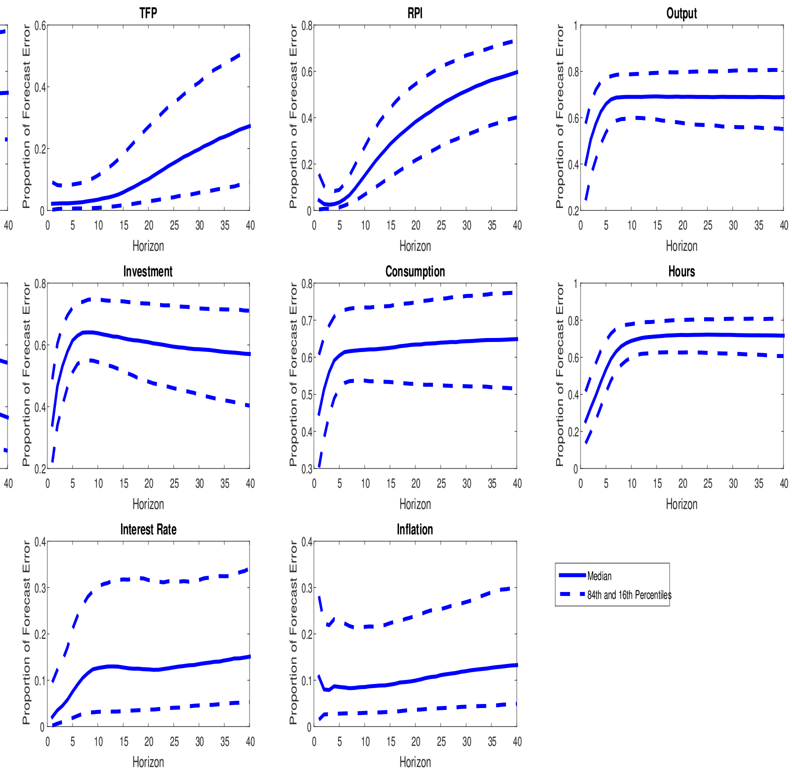
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing RPI with Fernald (2014)'s Investment TFP measure. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing RPI with Fernald (2014)'s Investment TFP measure.

Figure 14: **PCE Deflator: (a) Impulse Responses; (b) Contribution to FEV.**



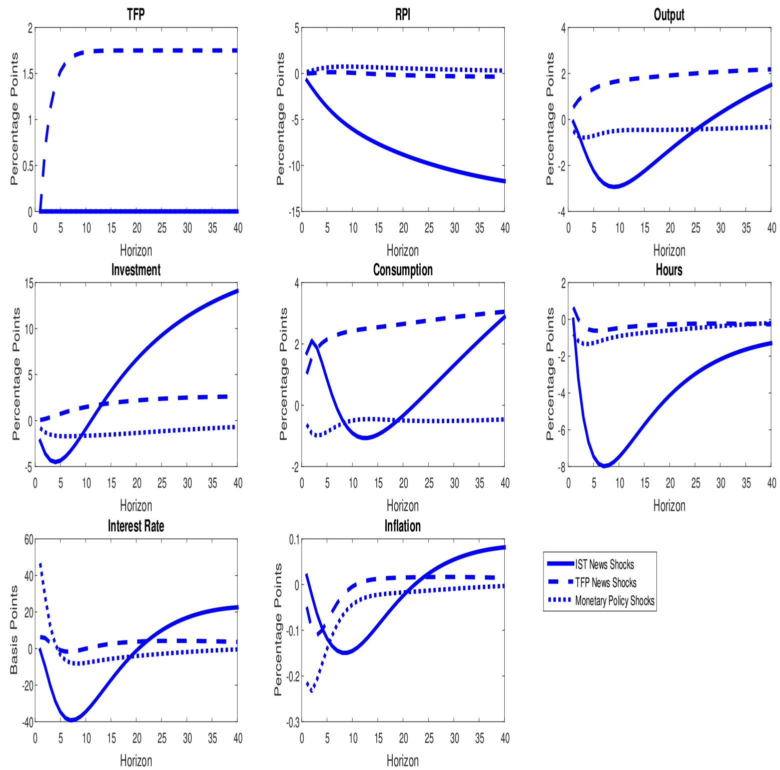
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



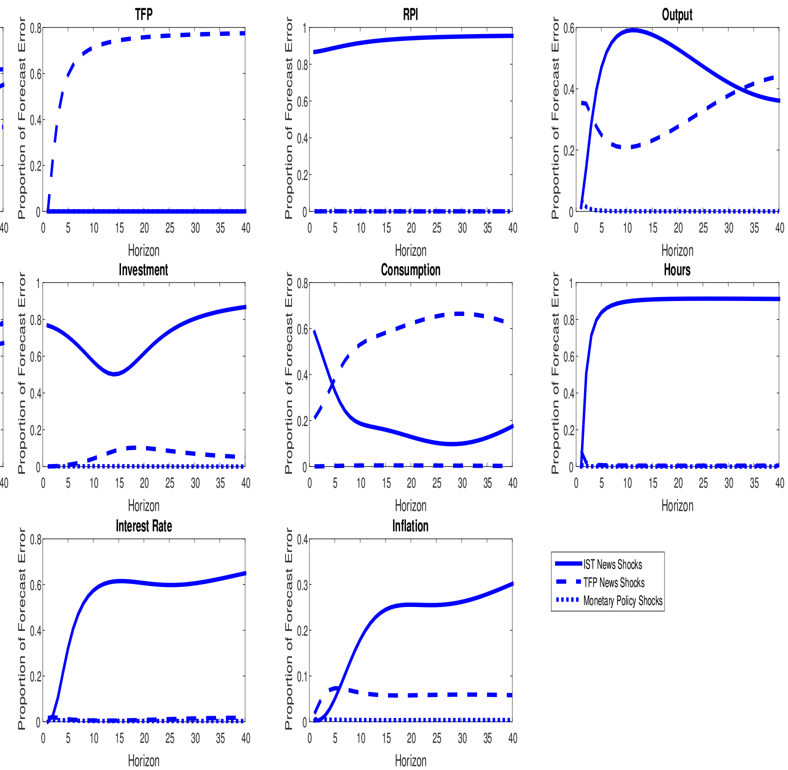
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the CPI-based inflation measure with the PCE-based one (log-first-differences of the PCE deflator). Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the CPI-based inflation measure with the PCE-based one (log-first-differences of the PCE deflator).

Figure 15: **DSGE Model: (a) Impulse Responses; (b) Contribution to FEV.**



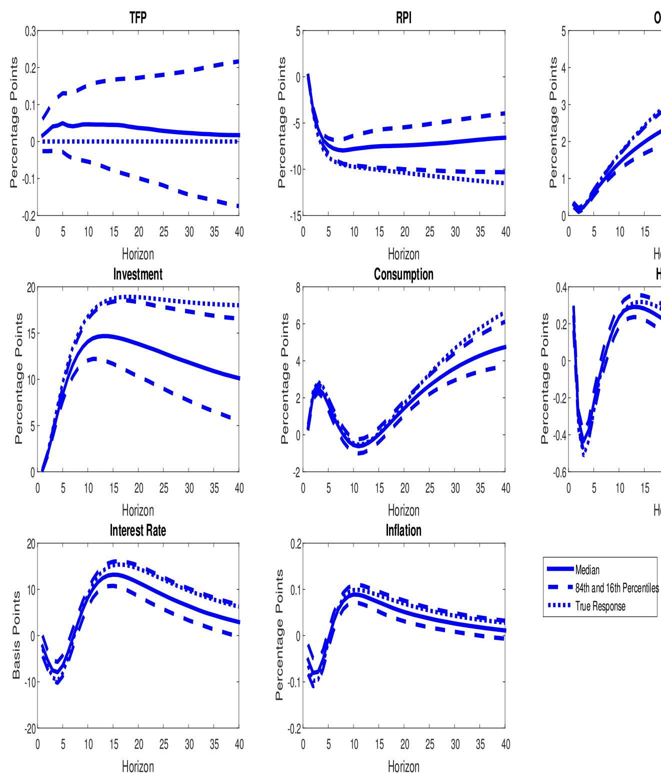
(a) Theoretical Impulse Responses to IST News, TFP News, and Monetary Policy Shocks.



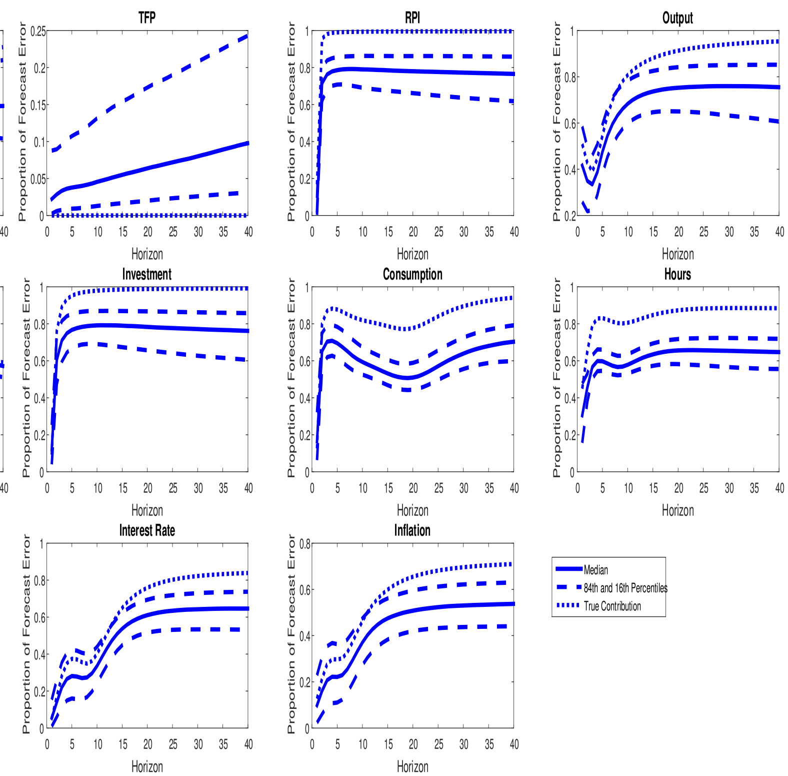
(b) Theoretical Contribution of IST News, TFP News, and Monetary Policy Shocks to the FEV of the Variables.

Notes: Panel (a): The solid, dashed, and dotted line are the impulse responses to IST news, TFP news, and monetary policy shocks, respectively, from the DSGE model (described in Appendix B) used for the Monte Carlo experiment from Section 5.1. Panel (b): The solid, dashed, and dotted line are the FEV contributions of IST news, TFP news, and monetary policy shocks, respectively, from the DSGE model (described in Appendix B) used for the Monte Carlo experiment from Section 5.1.

Figure 16: **Monte Carlo Evidence from a DSGE Model: Baseline Estimation Procedure: (a) Impulse Responses; (b) Contribution to FEV.**



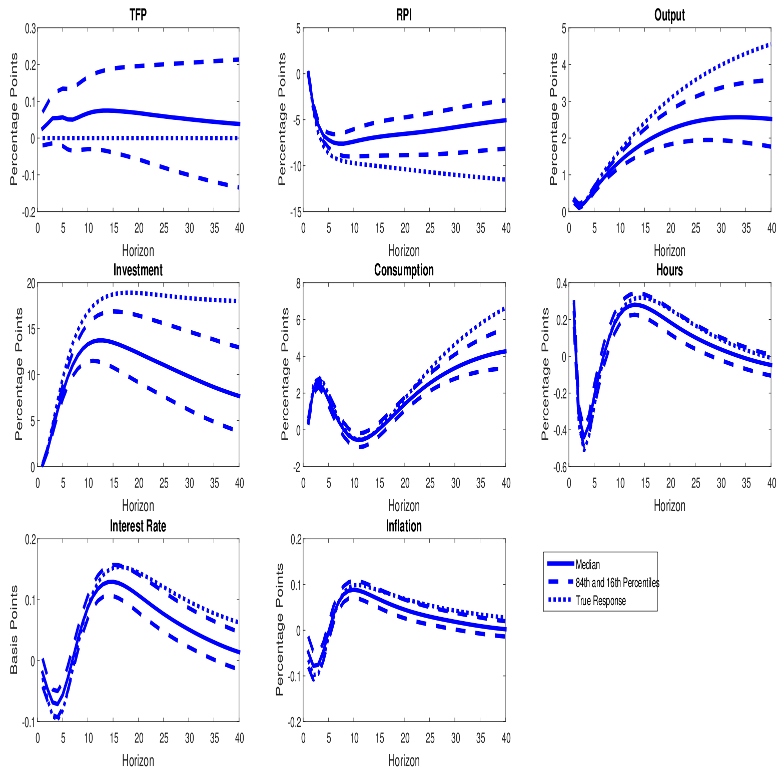
(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



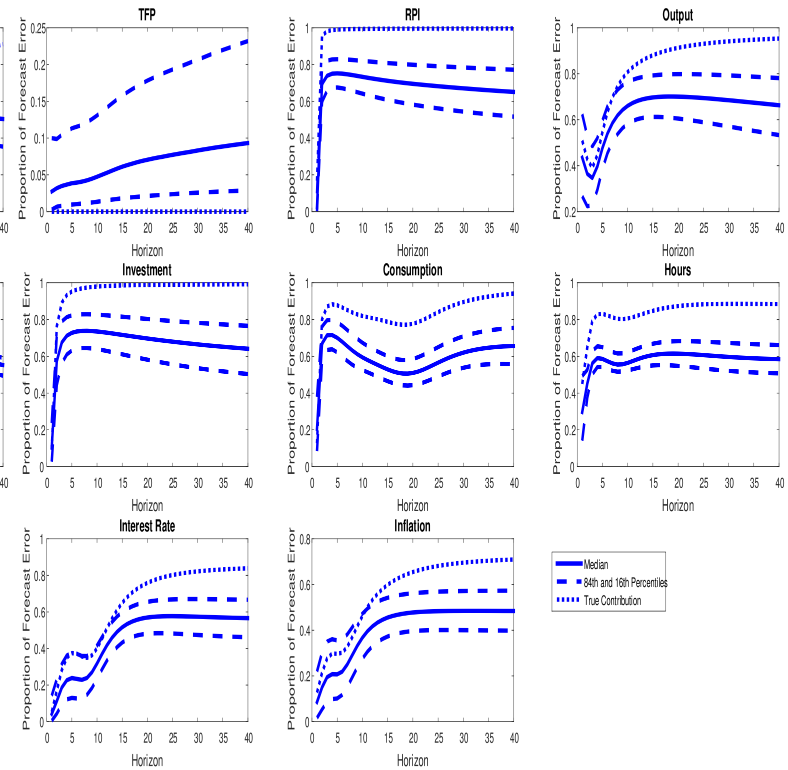
(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying the baseline estimation procedure to artificial data sets generated from the DSGE model described in Appendix B with the alternative calibration from Section B.10. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.

Figure 17: **Monte Carlo Evidence from a DSGE Model: Estimation Procedure Without Long-Run Restriction: (a) Impulse Responses; (b) Contribution to FEV.**



(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying an estimation procedure that excludes the long-run Restriction 2 to artificial data sets generated from the DSGE model described in Appendix B with the alternative calibration from Section B.10. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.