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.

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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 real 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 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

[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. (The rather conservative 90% threshold, as opposed to the ideal 100% one, is mainly motivated by the possibility of measurement error in RPI.)

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 shocks 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 shocks 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 to the true data generating process, I also impose that at least 90% of the long-run variation in RPI is driven by two shocks.[7] Hence, the methodological approach employed in this paper can be

[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.

[7] At the end of Section 3, I demonstrate that the business cycle shock's structural interpretation advanced

viewed as an amalgamation of previously used approaches.

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 restrictions accord 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.

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. 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

in this paper is robust to removing this long-run restriction.

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 progress with the relative price of investment:

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

where a_j stands for the capital share in sector $j = C, I$; $mc_{j,t}$ is real marginal cost (or the inverse of the equilibrium markup) in sector $j = C, I$; $K_{j,t}/L_{j,t}$ represents the capital-labor ratio in sector $j = C, I$; $\frac{P_{I,t}}{P_{C,t}}$ 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 (i.e., Basu et al. (2010) and Justiniano et al. (2011)) 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.[8] This is the underlying identifying assumption made by papers that aimed to

[8]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.

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 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:[9]

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

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

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. 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.

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.

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

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 measurement errors which lead to a violation of the aforementioned identifying assumption.[10] 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

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

[10]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.

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.

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.[11]

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 aggregates, i.e., output, hours, consumption, and investment, and explains at least 50% of the

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

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 contain 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. 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.) 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 real-time, 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 directly 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 in the non-farm business sector, consumption as the sum of non-durables 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

[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.

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 variance 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 and durables, non-durables and services 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. 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)).[15] 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 of models). Figures 1a and 1b depict the median and 84th and 16th percentiles of the posterior distributions of impulse responses and contribution to forecast error variance (FEV) 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

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

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

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 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, it is apparent 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 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%.[16,17] 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.[18] 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.

Boom-bust Behavior of the Shock in the Late 1990s and 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 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

[16]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 shocks is 0.8, we can deduce that $\omega_1^2 = 0.8$. But since $\omega_1 + \omega_2 = 1$, we obtain that $\omega_2 = 1 - 0.8^{0.5} = 0.09$.

[17]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 strong persistence in the impulse response of RPI and TFP, the 10 year estimates are downward biased estimates of the long-run response estimates.

[18]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.

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.[19] It is apparent that a clear boom-bust pattern is prevalent in the business cycle shock series where the average shock 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 previous figures demonstrate that the business cycle shock exhibits an apparent 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

[19] In 1233 models out of the set of admissible 1297 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.

results from Table 3 show how much in percentage terms of the movement in investment in the boom and bust periods is accounted for by the two shocks.[20] 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.[21] 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 shocks 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 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, and that the business cycle shock's IST-news-based structural interpretation is robust to removing the long-run restriction (restriction 2).

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

[20] 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 increase 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.

[21] 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.

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),[22] 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 4 shows the correlations between the HP trends of log and log-first-differences of hours worked and HP trends of first-log-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

[22]The actual long-run associated impulse responses and FEV contributions are available upon request from the author.

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 4 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.[23]

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

[23] 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 real 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 from the differenced specification applied to real 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.

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.[24]

Figures 3a and 3b show the mean estimated median and 16th and 84th 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 contribution to the FEV 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 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

[24] 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.

based on correctly specifying hours in levels in the estimated VARs. Clearly, the mean estimated median responses and contribution to FEV 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 2 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. 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 2. 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 Table 5 depicts the long-run impulse response and FEV contributions of the business cycle shock and Table 6 presents its mean realizations of 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 6, 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. (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.)

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. Although the business cycle shock does not explain the long-run variation in RPI as much as it does in the baseline case, leaving more room to argue for a TFP news component being present in this shock, the clear boom-bust pattern exhibited by the business cycle 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 paper.[25]

4 Robustness Checks

This section examines the robustness of the baseline results along three main dimensions.[26] 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. And the third relates to the

[25] 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 in the bust period is even more positive.

[26] I have also confirmed that the main results of the paper are robust to different numbers of lags in the VAR. These results are available upon request from the author.

inclusion of stock prices in the VAR.

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 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.[27] 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 7 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 7 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 quantita-

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

tive 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.

Results for Post-1982 Sub-Sample. One may be concerned that the VAR coefficients may not be stable over the entire sample period. Moreover, the VAR innovations may not be homoskedastic. 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 heteroskedasticity (see, e.g., Stock and Watson (2007)), are essentially the same as the large sample results.

Figures 6a and 6b show the impulse response and FEV contributions from this exercise; and the third and fourth rows of Tables 2 and 3 depict 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.

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 impact 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 third and fourth rows of Tables 2 and 3 depict the shock's mean realizations of the boom-bust period and its contribution to the variation in investment over this period, respectively. Moreover, Table 8 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 8 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.[28] Overall, the results support the interpretation of the business cycle shock as representing an IST news shock.

5 Conclusion

This paper has made an important contribution to our understanding of the underlying source of business cycles by providing 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 busi-

[28]Relative to steady state growth as computed from the sample 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.

ness cycle variation in the latter real aggregates. Then, I examined the common features of this 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 being 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.

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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%]

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. 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]

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:Q1-2003Q1) periods. Results for the baseline VAR, as well as alternative model specifications, 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; for the post-1982 VAR, results on this shock are based on 1972 such models; and for the VAR with stock prices, results on this shock are based on 261 such models.

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%]

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 (2001:Q1-2003Q1) periods. Results for the baseline VAR, as well as alternative model specifications, 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 for investment for the full and post-1982 samples are assumed to be 2.8% and 3.3%, respectively, which are the average growth rates for the corresponding sample periods. Note that a relative contribution of 100% implies that all of the gain or loss in investment is accounted for by the shock. See notes from Table 2 for details on the set of models on which the results on the other long-run RPI shock are based.

Table 4: **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 5: **Lifting the Long-Run Restriction: Long-Run Implications of Business Cycle Shock for RPI and TFP.**

	Impulse Response	Forecast Error Variance Contribution
RPI	-1.5% [-3.2%,-0.7%]	44% [12%,69%]
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 6: **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
Boom Period	0.51 [0.38,0.64]	85% [53%,120%]
Bust Period	-0.35 [-0.54,-0.17]	166% [102%,229%]

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 (2001:Q1-2003Q1) 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.

Table 7: **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

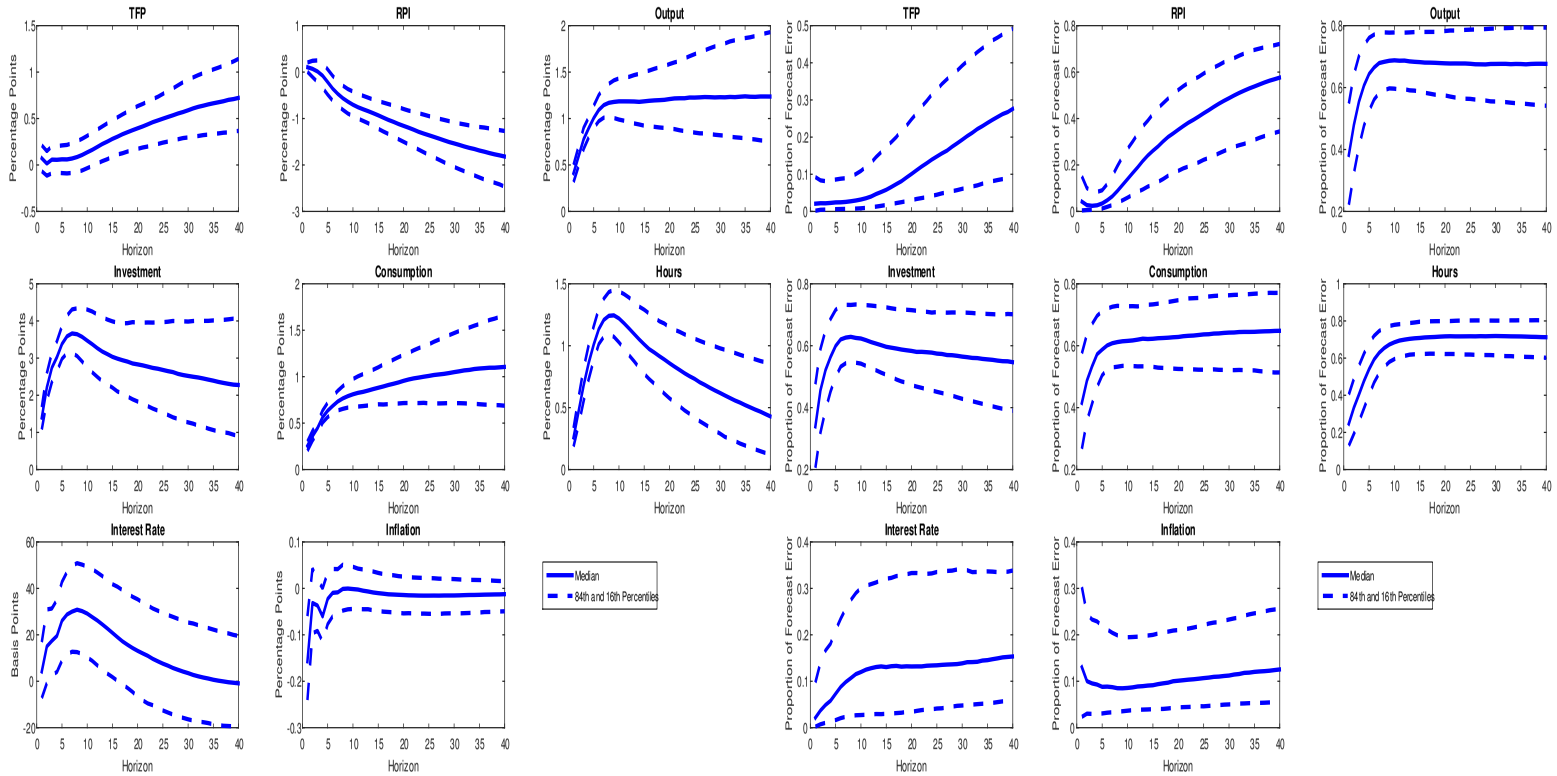
Notes: Column n reports the p-value of the F-test of the regression of the median business cycle shock series on three lags of the first n principle components extracted from the FRED-QD comprehensive quarterly data set, where n goes from 1 to 8.

Table 8: **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 (2001:Q1-2003Q1) 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. See notes from Table 2 for details on the set of models on which the results on the other long-run RPI shock are based.

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

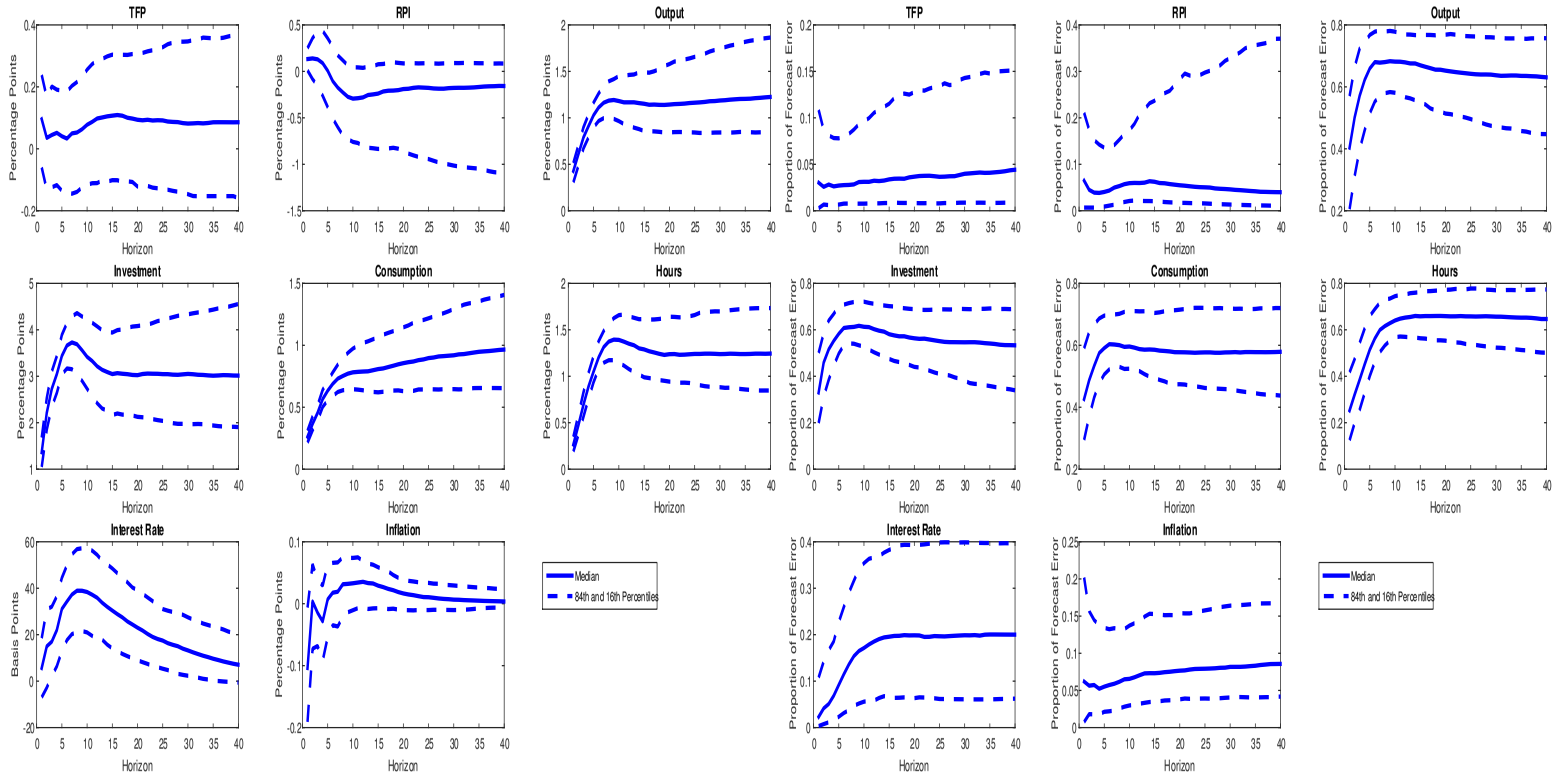


(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.

(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**

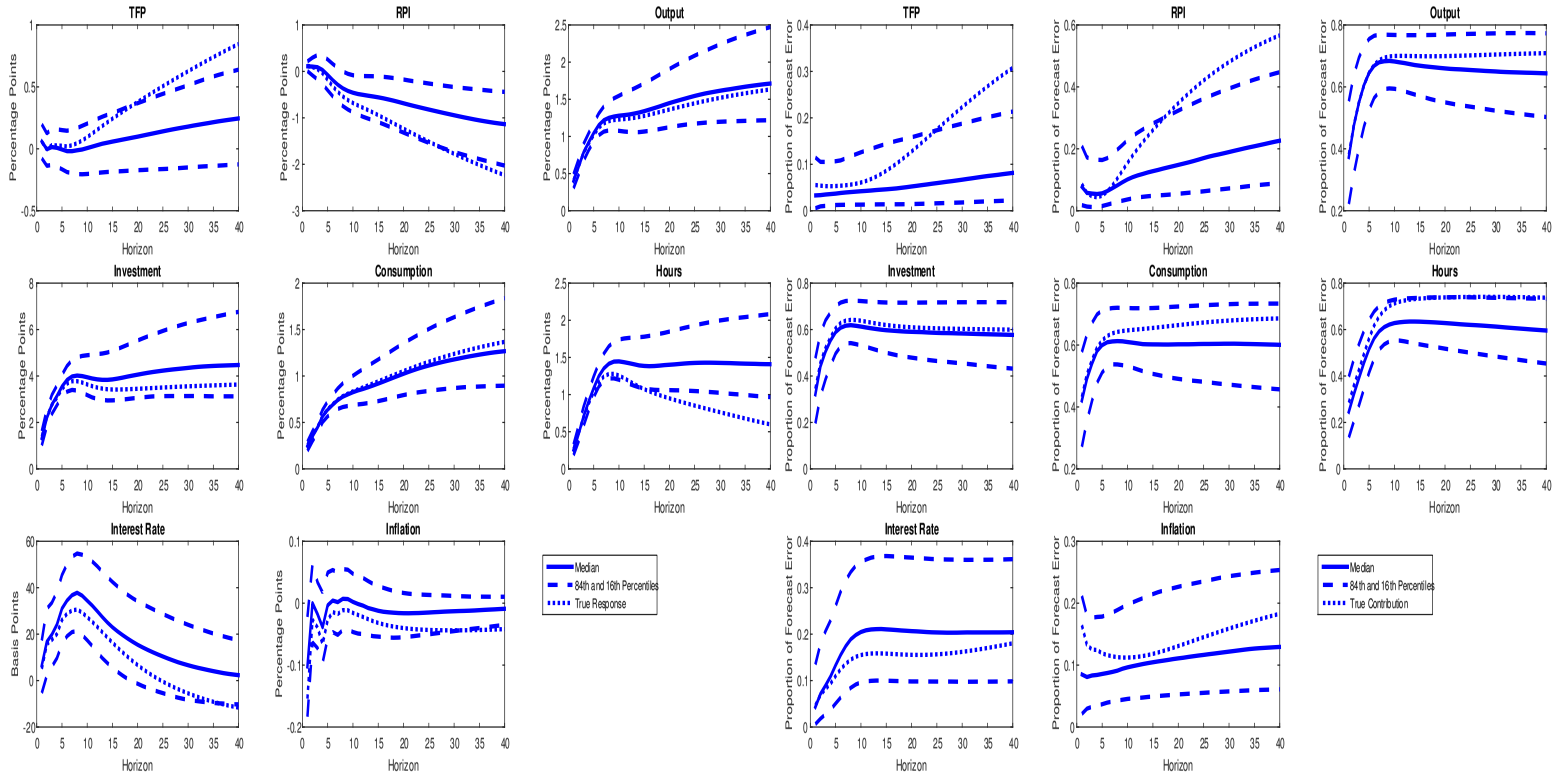


(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.

(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.

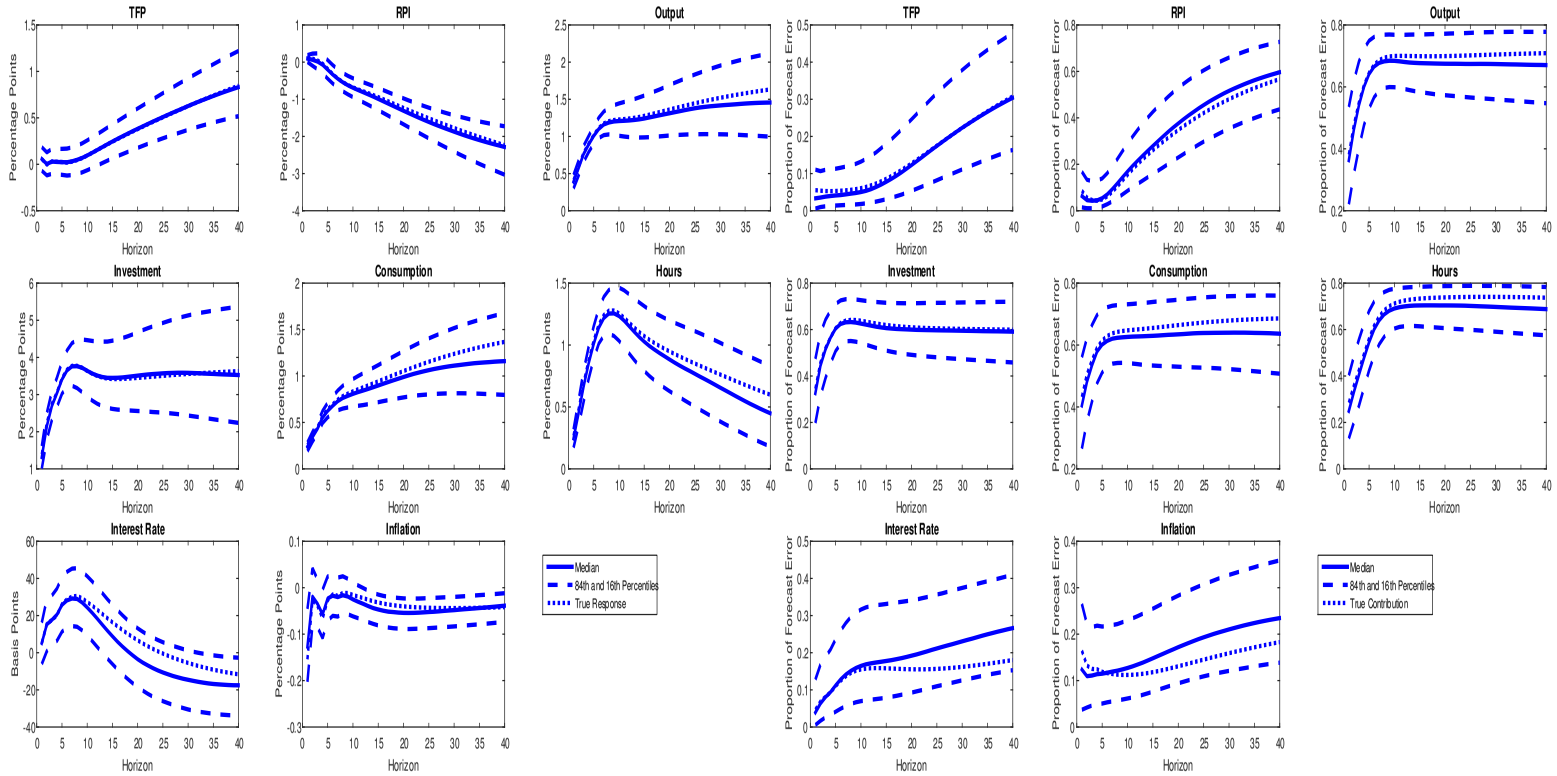
Figure 3: **Monte Carlo Evidence from a Non-Stationary Hours Specification: (a) Impulse Responses ; (b) Contribution to FEV**



(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**

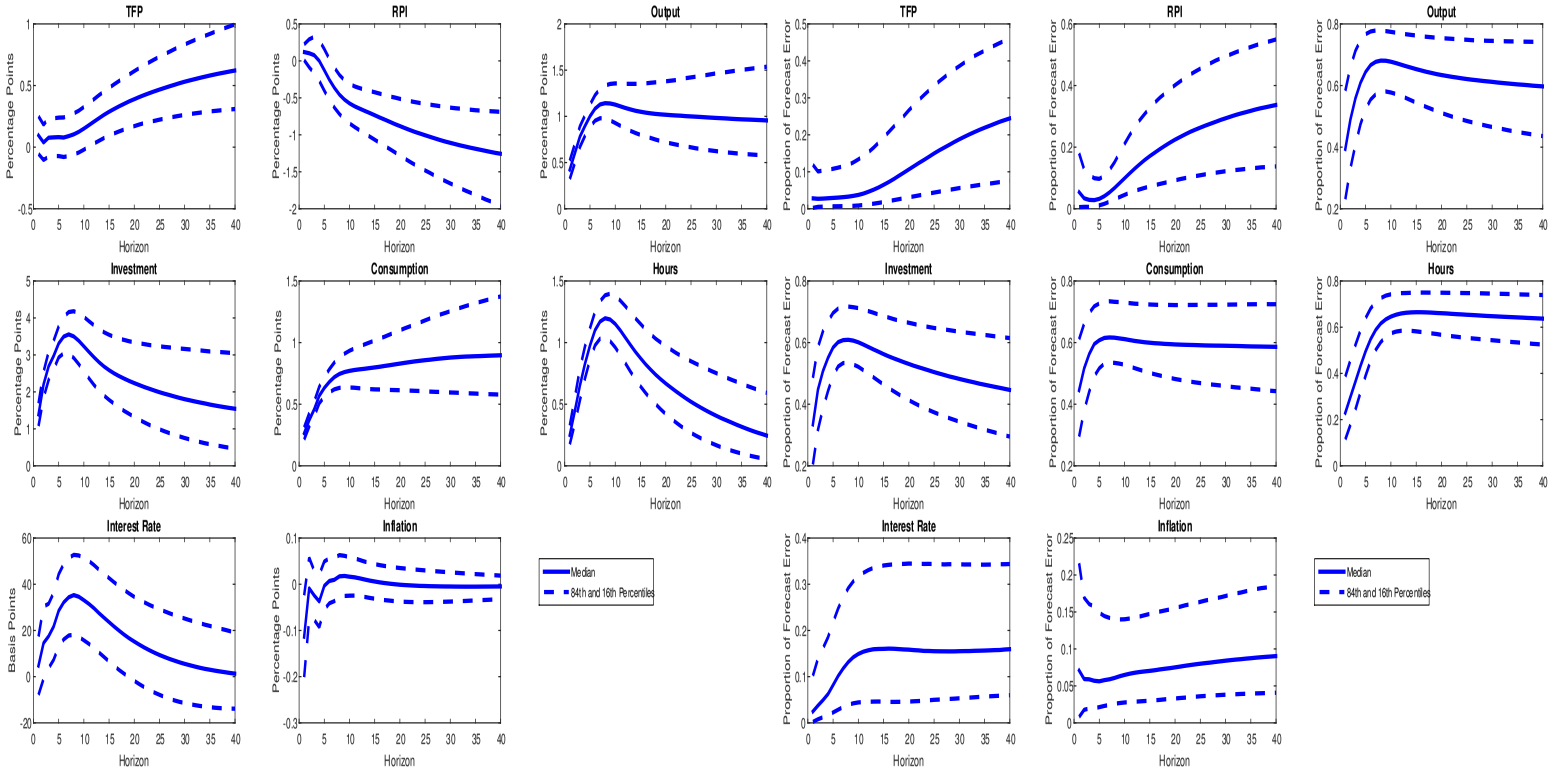


(a) The Mean Estimated Median and 84th and 16th percentile Impulse Responses and the Mean True Impulse Responses.

(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**

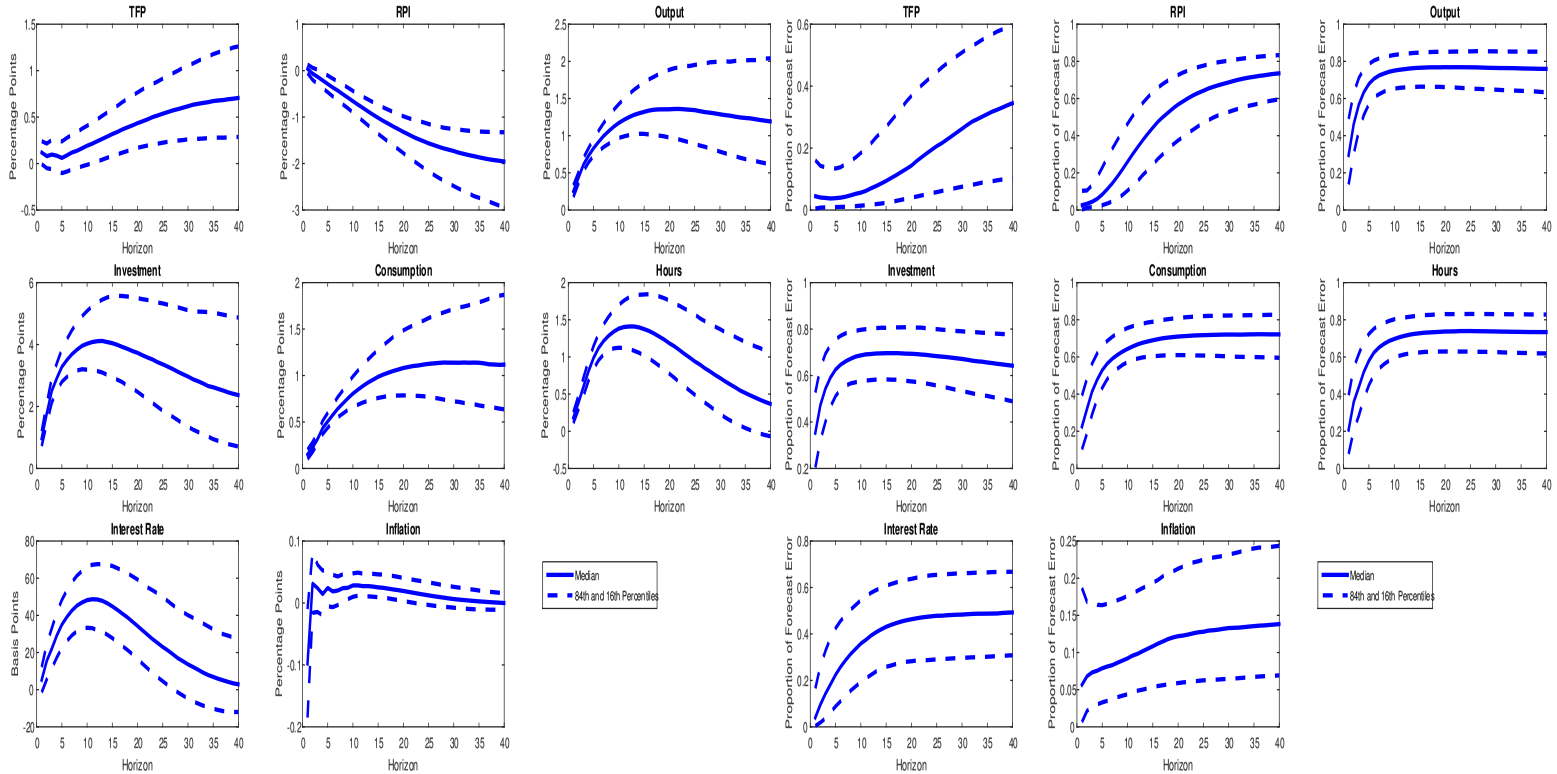


(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.

(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**

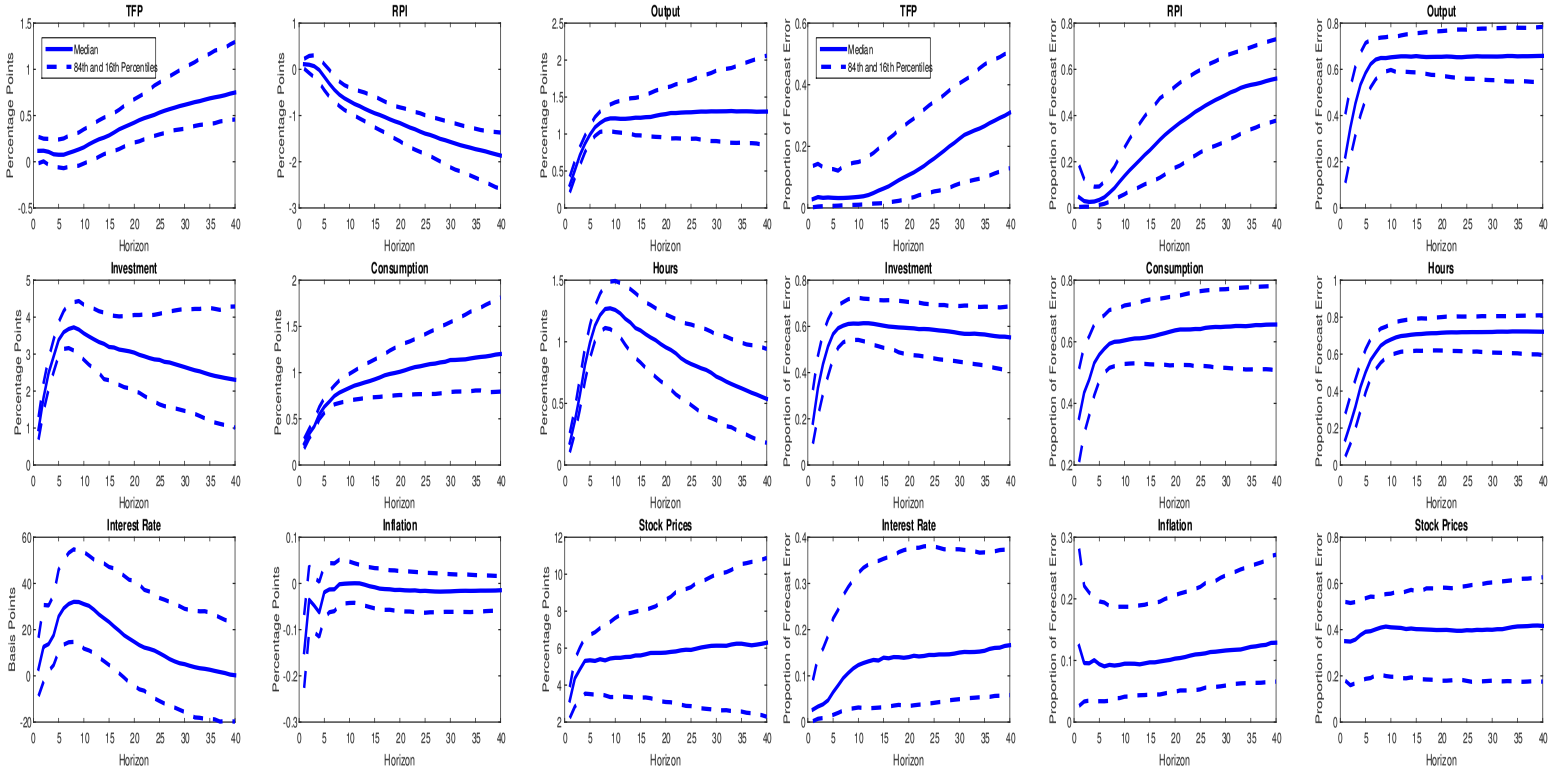


(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.

(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 FEVcontributions 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.