**WHAT CAN WE LEARN ABOUT
NEWS SHOCKS FROM THE
LATE 1990s AND EARLY 2000s
BOOM-BUST PERIOD?**

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What Can We Learn about News Shocks from the Late 1990s and Early 2000s Boom-Bust Period?[*]

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Abstract

The major boom-bust period of 1997-2003 is commonly viewed as an expectations-driven episode in which overly optimistic expectations about information and communications technology were followed by their downward revision. This paper employs a novel approach to identifying the news shocks of this period that restricts the identified shock to have its maximal three-year moving average of realizations in the 1997-1999 boom period, followed by a negative average in the bust period. I provide robust evidence that this shock raises output, hours, investment, and consumption, and accounts for the majority of their business cycle variation.

JEL classification: E32

Key words: business cycles; investment-specific technology; news shocks; boom-bust period

1 Introduction

The 1997-2003 period was a significant boom-bust period in the U.S economy, which is commonly viewed as an episode driven by overly optimistic expectations about information and communications technology (ICT) and the subsequent downward revision of these expectations (e.g., Jaimovich and Rebelo (2009) and Dupor and Mekhari (2011)).[1] Figure 1 depicts some data that are indicative of this special episode. The figure shows the monthly Shiller's cyclically adjusted price-earnings (CAPE) ratio, defined as the ratio of the real S&P 500 to the trailing 10 year real S&P 500 earnings, for the period of 1881:M1-2012:M6. It is apparent that the 1997-1999 boom period was a period of extremely high CAPE ratios; the beginning of 1997 marked the outset of unprecedented CAPE ratio levels in post-World War II era terms, exceeding the very high levels that prevailed during the 2004-2007 period. The remarkable rise of the CAPE ratio in the boom period culminated in an all-time high value of 44.2 in December of 1999, from which point it started its bust phase reaching a trough of 21.1 in February 2003.

The strong connection between ICT and technology in the broader sectors of durable goods allows to exploit this special boom-bust episode to identify investment-specific technology (IST) news shocks.[2] In the presence of news shocks, the standard long-run restriction (e.g., Fisher (2006) and Canova et al. (2010)) that posits that IST is the sole driver of the relative price of investment (RPI) in the long run implies that two shocks drive the long-run variation in RPI, one being the traditional unanticipated IST shock and the other being the IST news shock, where the news shock has no effect on current IST but rather portends future changes in it. Within a Bayesian Vector Autoregression (VAR) framework, I propose a novel identification approach that utilizes both the standard long-run assumption and the information on the 1997-2003 boom-bust period to identify

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[1]See Appendix A in Karnizova (2012) for a list of several extracts from academic and government publications that link the boom and the recession to a downward revision of overly optimistic expectations regarding ICT.

[2]The vast IST literature (e.g., Greenwood et al. (1997, 2000), Fisher (2006), Canova et al. (2010), Beaudry and Lucke (2010), and Liu et al. (2011)), which began with the pioneering work by Greenwood et al. (1988), focuses on technology in the equipment and software investment and consumer durable goods sectors, of which ICT is an important component. In particular, nominal expenditures on information and communication equipment have accounted for roughly one half of the overall investment in equipment and software since the late 1990s.

IST news shocks by restricting the identified news shock to i) have a long-run effect on RPI and ii) have its maximal three-year moving average of realizations in the 1997-1999 period followed by a negative average in the bust period, where the absolute value of the sum of realizations in the bust period is at least 25% of the boom period sum. To account for the unanticipated IST shock, I allow for an additional shock to have a long-run effect on RPI by restricting the long-run variation of RPI to be driven by two economic shocks, i.e., the boom-bust shock identified as the IST news shock and the additional shock identified as the unanticipated IST shock. The restriction on the 1997:Q1-1999:Q4 sub-series dictates that the sum of shock realizations in the 1997-1999 period be larger than any other three-year period sums and manifests the view that this period is plausibly the most apparent IST news-driven episode in post-war data. Moreover, the restriction on the 2000:Q1-2003:Q1 sub-series implies that at least a 25% correction of expectations took place in the bust period. This seems a reasonable threshold given that essentially all of the stock market gains in the boom period were lost in the bust period.[3]

I apply the identification strategy to a VAR that contains RPI, the real aggregates (output, hours, investment, and consumption), inflation, and interest rates, and find that the identified IST news shock raises the real aggregates and accounts for the majority of their business cycle variations. Moreover, this shock raises interest rates, lowers inflation, and accounts for the bulk of the long-run variation in output, consumption, and RPI. These benchmark findings are shown to be robust to various alterations and extensions of the baseline model, e.g., different sample periods, alternative RPI measures, and estimating a variety of larger VAR's that include additional important macroeconomic variables such as stock prices, credit spreads, and total factor productivity (TFP).

Beaudry and Portier (2004) and Karnizova (2012) have emphasized the view that the news shocks that took place in the late 1990s embodied expectations about the future expected economy-wide gains from using the new and improved ICT. According to this view, the late 1990s news shocks portended a future increase in measured TFP via the use of better capital goods resulting from

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[3]The results of this paper are insensitive to imposing different correction thresholds.

improved ICT. To check the validity of this view, I add to the benchmark VAR the utilization-adjusted TFP measure constructed in Fernald (2012) and apply my identification method to this extended VAR. The results from this exercise indicate that the identified IST news shocks have a small effect on TFP at all horizons, casting doubt on the relevance of the TFP news view of the late 1990s and early 2000s period. Moreover, it is important to note that this outcome is not driven by the presumption that the IST news view of this period is valid. In particular, I also ran an exercise in which the identified shock complied with the boom-bust restriction but was restricted to be a non-IST shock, i.e., it was restricted to have no long-run effect on RPI, and found that the non-IST boom-bust shock is unrelated to TFP at all horizons. That is, the result that the TFP news-view is not supported by the data is independent of whether or not the IST news view is presumed.

The results of this paper pose a challenge for DSGE model builders to try to construct models in which IST news shocks are not only capable of generating business cycles but are also the main driver behind business cycle fluctuations. While the former feature has already been obtained by papers such as Jaimovich and Rebelo (2009) and Dupor and Mekhari (2011), the latter feature is much harder to generate in DSGE models. In particular, in the estimated DSGE models of Khan and Tsoukalas (2011) and Schmitt-Grohé and Uribe (2012) IST news have a very limited role. Moreover, that IST news shocks imply a significant long-run increase in IST which in turn drives a significant permanent increase in output and consumption is consistent with the view taken in Greenwood et al. (1997) that IST is an important driver of long-run growth. The novelty of this paper's results is that it is the news shock component of IST which is driving long-run growth, rather than the unanticipated shock.

There are two main streams of literature to which my paper is linked. First, from a methodological standpoint, the identification 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 theory-consistent restrictions are imposed to generate a set of theory-consistent models.[4]

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[4]It is worth noting that this paper uses the efficient identification algorithm developed by Rubio-Ramirez et al. (2010) which correctly draws from the posterior distribution of structural parameters conditional on the sign restrictions, as opposed to using the penalty function approach employed in Mountford and Uhlig (2009) and Beaudry et al. (2011) which selects a single value of the structural parameters by minimizing a

This literature has mainly focused on imposing restrictions on the sign of impulse responses (e.g., Uhlig (2005), Dedola and Neri (2007), Mountford and Uhlig (2009), Peersman and Straub (2009), Helbling et al. (2011), and Kilian and Murphy (2012)) as well as the sign of the cross correlation function in response to shocks (Canova and De Nicolo (2002)). My method is new with regard to the sign restrictions literature in two important respects. First, it does not impose restrictions on the effects of the shocks but rather on the shock realizations themselves. Second, it imposes restrictions on the long-run forecast error variance decomposition of RPI. The long-run restriction ensures that only two shocks drive the long-run variation in RPI, whereas the boom-bust restriction enables one to distinguish between unanticipated and news shocks and to identify both shocks. The long-run restriction can be considered a robust model-based restriction as, in most IST-driven models, the long-run variation in RPI is entirely driven by IST. The boom-bust restriction, while not being rooted in any macroeconomic model, is based on a real macroeconomic event and its plausible interpretation, which is shared by various economists.

Second, my paper is related to the literature on IST news shocks. While Khan and Tsoukalas (2012) and Schmitt-Grohé and Uribe (2012) identified these shocks via an estimated DSGE model and found a negligible role for them in the business cycle, Ben Zeev and Khan (2015) obtained results that are fairly similar to those found in this paper by applying a very different identification approach based on the Barsky and Sims (2011) maximum forecast error variance (MFEV) identification approach to news shocks. In particular, Ben Zeev and Khan (2015) identified the IST news shock as the shock orthogonal to RPI and which maximally explains future short-run and medium-run movements in RPI. While the Barsky and Sims (2011) MFEV method requires observing the fundamental to which the news shock pertains, exploiting the IST news-driven episode of the late 1990s and early 2000s enables me to identify IST news shocks without assuming that IST is fully reflected by RPI and is thus observable, as is the case in Ben Zeev and Khan (2015).[5]

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loss function. Hence, this paper is not susceptible to the criticism recently put forward by Arias et al. (2014) who show that the identification procedure used in Mountford and Uhlig (2009) and Beaudry et al. (2011) introduces additional sign restrictions that bias the results and produce misleading confidence intervals.

[5]The median correlation between this paper's identified shocks and the Ben Zeev and Khan (2015) shock series is 58%, a significant correlation though clearly one that manifests a noticeable wedge between the two identified shock series. This wedge is to be expected given the fundamental difference between the types of

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 discusses the issue of how to interpret the identified news shocks on the basis of real-life news events. The final section concludes.

2 Identification Method

Prior to presenting the identification method in detail, I will first explain the underlying theoretical framework upon which the empirical analysis is based.

2.1 Underlying Framework

The general relation between RPI and IST can be illustrated by considering a two sector model along the lines outlined in Justiniano et al. (2011) with separate imperfectly competitive investment and consumption sectors. Both sectors are influenced by a common total factor productivity (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

identification restrictions imposed in the two identification strategies.

(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.

Nevertheless, it is quite reasonable to assert that IST is the sole source of the long-run variation in RPI. For this assertion to be true, 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 shares for the services and non-durables sector and the equipment and software investment and consumer durables sector are 0.36 and 0.31, respectively. 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 the long-run variation in RPI is driven by IST. This is the underlying identifying assumption made by papers that aimed to identify unanticipated IST shocks (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. However, 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.

IST is assumed to be 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 IST. The following is an example process that incorporates both unanticipated and IST news

shocks:[6]

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

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

Here the log-deviation of IST from its steady state, denoted by ϵ_t, follows a unit root process where the drift term itself g_{t-1} follows an AR(1) process with an anticipation lag of one period, i.e., there is a delay of one period 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; and v_t can be defined as an IST news shock, given that the timing assumption implies that it has no immediate impact on the level of IST but portends future changes in it.

Note that the news process described by Equations (2) and (3) does not imply that IST news shocks always materialize eventually; it merely implies that IST news shocks always materialize *on average*. This is true regardless of whether the information structure is such that agents only receive noisy signals about the true underlying news shocks or rather directly observe them. Either way, news shocks will fully materialize only on average as future realizations of both η_t and v_t are zero in expectation. Thus, within this general framework there can be periods in which news shocks fail to fully materialize due to being counteracted by an ex-post revision of expectations (i.e., negative realizations of subsequent news shocks), which is what is usually argued to have been the case for the late 1990s and early 2000s period.

Given the above underlying theoretical framework, I will only consider models that are consistent with Equation (1). In particular, I will 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

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[6]A similar process was used by Leeper and Walker (2011), Barsky and Sims (2011, 2012), and Leeper et al. (2013). The stochastic drift term g_t is introduced so as to generate a smooth news process whereby following the news shock technology will start to rise one period into the future after which it will continue to gradually and persistently increase until reaching some new higher steady state. If κ were to equal zero there would be no gradual rise but rather a jump in technology one period into the future after which technology will remain at that higher level permanently.

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. I now turn to explaining the empirical strategy employed in the paper.

2.2   Generating the Set of Admissible Models

The methodology is a set identification VAR-based method which generates the set of 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 solution or a set of solutions. As will be explained below, this set of solutions will constitute the set of models that satisfy my imposed restrictions. I employ Bayesian estimation and inference and therefore the set of admissible models will also account for parameter uncertainty. My benchmark empirical VAR consists of the real aggregates, 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_i 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 $(kp + 1)$xk matrix $B = [B_1, ..., B_p, B_c]'$ represent the reduced form VAR coefficient matrix. Hence, the reduced form VAR parameters can be summarized by the stacked 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 as:

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

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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 ($D' = D^{-1}$, which entails $D'D = DD' = I$ where I is the identity matrix).[7]

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 orthonormal matrices D in order to generate a large set of models from which the set of admissible models can be obtained by checking which models comply with the imposed restrictions. I follow the conventional Bayesian approach to estimation and inference taken by the sign restrictions literature (e.g., Uhlig (2005), Peersman and Straub (2009), and Kilian and Murphy (2012)) by jointly drawing from the posterior distribution of the reduced form VAR parameters, summarized by matrices B and Σ, and identification matrices D under the standard assumption of a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters and a Haar distribution for the identification matrix. As shown by Uhlig (1994), the normal-inverse Wishart prior coupled with the assumption of a Gaussian likelihood for the data sample imply a posterior density of the reduced-form VAR parameters that is also distributed as a normal-inverse Wishart.[8] The procedure for randomly drawing models can be described as follows:

1. Randomly draw a kxk matrix P of NID(0,1) random variables. Derive the QR decomposition of P such that $P = QR$ and $QQ' = I$ and let D=Q.

2. Randomly draw from the posterior distribution of reduced form VAR parameters $p(B, \Sigma \mid data)$. Compute the Cholesky factor of the drawn Σ and denote it by C.

3. Use orthonormal matrix D, Cholesky factor matrix C, and coefficient matrix B to compute

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[7] In accordance with the SVAR literature, I assume here that the number of economic shocks is equal to the number of observables.

[8] It is worth noting that because D does not appear in the likelihood function its prior and posterior distributions are the same, both being represented by the Haar distribution.

impulse responses and economic shocks via the orthogonalization $A = CD$.

4. Repeat steps 1-3 10^6 times.

Steps 1 and 2 are needed to draw the identification matrix D and reduced form VAR parameters B and Σ, respectively. Appendix A describes the details of how the posterior simulator for the reduced form VAR parameters is implemented. As discussed by Rubio-Ramirez et al. (2010), Step 1 constitutes an efficient method for generating orthonormal matrices. Step 3 involves using the drawn matrices from the previous two steps and the orthogonalization $A = CD$ for the computation of the impulse responses and economic shocks, computed as $e_t = A^{-1}u_t$. Steps 1-3 essentially deliver a matrix triplet (B,Σ,D) which represents a model as this matrix triplet is all that is needed for knowing the corresponding model in terms of impulse responses, forecast error variance decomposition, and series of economic shocks. I generate 10^6 such matrix triplets, or models, in accordance with Steps 1-3, from which only the admissible models are chosen so as to constitute the desired set of models that are compliant with my restrictions. In practice, it is checked if the resulting models comply with the following restrictions:

1. One shock, belonging to the vector of economic shocks e_t, has its maximal three-year moving average of realizations in the 1997-1999 period followed by a negative average in the bust period of 2000:Q1-2003:Q1, where the absolute value of the sum of realizations in the bust period is at least 25% of the boom period sum.

2. At least 90% of the long-run variation in RPI is driven by the shock from the first restriction and an additional arbitrary shock belonging to e_t.[9]

To be clear, the maximum in Step 1 is computed with respect to all of the three-year sub-series within the same shock series. Hence, this restriction implies that the sum of realizations in the 1997-1999 period is larger than the sum of realizations in all other three-year periods present in

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[9] To ensure that the identified shock is not a measurement error or some other economic shock that also experienced large realizations in the boom period (e.g., noise shocks), I also imposed the restriction that the identified shock explain at least 5% of the long-run variation in RPI. Nevertheless, this had a negligible effect on the results as in only one percent of the admissible models did the identified shock explain less than 5% of the long-run variation in RPI.

the shock series. Given a shock series of size $T - p$, where T is the sample size for the observed variables and p is the number of lags in the VAR, this maximum restriction essentially implies a total of $T - p - 11$ inequality restrictions on the shock series.

The chosen boom and bust periods are generally consistent with the boom and bust behavior of both the stock market as well as the real economy. The boom restriction essentially requires that the largest realizations of IST news shocks take place in the boom period, in accordance with the common view that the boom period is the most apparent IST news-driven period in post-war data. Note that the choice of the starting and ending periods of the boom period is consistent with the fact that in the beginning of this period the stock market, as measured by Shiller's CAPE ratio, started to reach unprecedented levels in post-war era terms, after which it rose continuously until peaking at the end of the period. The bust restriction requires that at least a 25% correction of the overly optimistic expectations of the late 1990s takes place in the early 2000's. This seems a reasonable threshold given that essentially all of the stock market gains in the boom period were lost in the bust period.

3   Empirical Evidence

In this section the main results of the paper are presented. Before proceeding, a brief discussion of the data is given.

3.1   Data

RPI is measured in the standard way as a quality adjusted investment deflator divided by a consumption deflator (e.g., Greenwood et al. (1997, 2000), Fisher (2006), Canova et al. (2010), Beaudry and Lucke (2010), and Liu et al. (2011)). The consumption deflator corresponds to nondurable and service consumption, derived directly from the National Income and Product Accounts (NIPA). 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: 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 deflator series constructed by Patrick Higgins at the Atlanta Fed that spans the period 1959:Q1:2012:Q1. I use this updated series as a measure for RPI.[10]

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 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 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 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. To convert monthly population, inflation, and interest rate series to quarterly series, I use the last monthly observation from each quarter. My benchmark data series span the period 1959:Q1-2012:Q1; the sample size is dictated by that of the GCV-deflator based RPI series.

3.2   Impulse Responses and Forecast Error Variance Decomposition

I apply my identification method on a VAR that includes seven variables: RPI, output, investment and durables, non-durables and services consumption, the log of total hours worked, CPI inflation, and interest rates. Apart from the log of hours, inflation, and interest rates, which are assumed to be stationary and enter the system in levels, all other variables enter the system in log-first-difference form. The Akaike information criterion favors three lags whereas the Schwartz and Hannan-Quinn information criteria favor one and two lags, respectively. As a benchmark, I choose to estimate a

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[10]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. In the next section which deals with robustness analysis, I confirm that the results are robust to using an RPI measure obtained directly from NIPA investment deflators.

VAR with three lags; the results are robust to using a different number of lags. 10^6 models are generated via the procedure described by Steps 1-4. I then check whether the identifying restrictions hold for each model and keep only the admissible models. The set of admissible models consists of 1635 models.

Figures 2a and 2b show the posterior distribution of impact impulse responses and contribution to forecast error variance (FEV) of the variables of the IST news shock at the two year horizon, respectively. Moreover, Figures 3a and 3b depict the median and 90th and 10th percentiles of the posterior distributions of impulse responses and contribution to forecast error variance at all horizons up to the 10 year one, respectively. In these figures, as well as all of the next figures, it was ensured that the identified IST news shock is a favorable shock by multiplying the impulse responses by -1 if the long-run effect of the shock on RPI was positive.

It is apparent from these four figures that favorable IST news shocks raise the real aggregates, reduce inflation, raise interest rates, and drive the bulk of the business cycle variation in the real aggregates.[11] The median impact effects on output, hours, investment, and consumption are 0.42%, 0.28%, 1.47%, and 0.28%, respectively. All of the latter effects are economically significant and point to the strong business cycle comovement that the IST news shock generates. The median contributions of IST news shocks to the variation in output, hours, investment, and consumption at the two year horizon are 64%, 65%, 60%, and 60%, respectively, all indicating that IST news shocks are the main force behind the business cycle.

The median contributions to the long-run variation in output, consumption, and RPI are 52%, 50%, and 78%, respectively, whereas that for investment is only 20%.[12] These long-run contributions indicate that IST news shocks have more of a hump-shaped effect on investment compared to

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[11]It should be noted that the unanticipated IST shock, identified as the other shock which drives the long-run variation in RPI, has a positive median effect on output, hours, and investment, a negative effect on inflation, and negligible effects on consumption and interest rates. Moreover, the shock has a small contribution to the business cycle variation of the real aggregates with median contributions to the two year variation in output, hours, investment, and consumption of 6%, 8%, 6%, and 4%, respectively. These results are available upon request from the author.

[12]Note that these estimates are not shown in Figures 3a and 3b as the latter 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.

output and consumption. Moreover, while IST news shocks don't account for much of the business cycle variation in RPI, they explain the bulk of its long-run variation.

3.3 Time Series of Identified Shocks

Figure 4 shows the median IST news shock series from the benchmark VAR. To make the figure more readable, I show the one year trailing moving average of the median shock series as opposed to the actual series. The smooth shock series was derived by first computing the median of the 1635 identified IST news shock series and then calculating the one year moving average series from the median shock series. The shaded areas represent recession dates as defined by the National Bureau of Economic Research (NBER). As the series starts in 1960:Q4, only the two last quarters of the 1960:Q2-1961:Q1 recession are included in the figure.

In accordance with the boom-bust restriction, there are significant positive realizations in the late 1990s followed by a series of negative realizations in the early 2000's and in particular in the 2001 recession. Moreover, significant negative IST news shocks are associated with all other seven U.S recessions included in the sample period. The evidence from Figure 4 is consistent with the results from the previous section which indicate that IST news shocks are a major driver of U.S business cycles.

4   Robustness

This section addresses eight potentially important issues regarding the analysis undertaken in the previous section. The first is the concern that there may not exist a perfect linear mapping between VAR innovations and economic shocks. The second issue pertains to the manner by which stock prices respond to the identified news shock, which a priori should be strongly instantaneous given this paper's interpretation of the identified shock as a shock that embodies information about future IST. The third is the concern that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The fourth issue pertains to the

possibility that hours are not necessarily stationary and thus should perhaps enter the system in log-first-differences rather than in levels. The fifth issue concerns the argument put forward recently by Justiniano et al. (2011) which asserts that there may be a relation between IST and credit market disturbances. The sixth issue concerns the notion that the news shocks that drove the boom-bust period portended a future increase in Total Factor Productivity (TFP) via the use of improved capital goods (e.g., Beaudry and Portier (2004)). The seventh potential concern is the robustness of the results to using alternative measures of RPI. Lastly, I also confirm that the results of this paper are not driven by other structural disturbances identified in the literature.[13]

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. Sims (2012) and Leeper et al. (2013) have highlighted that the presence of news shocks about future fundamentals can pose difficulties for an econometrician drawing inference based on identified VARs. Specifically, news shocks also constitute unobserved state variables and can therefore drive a wedge between VAR innovations and economic shocks if the observables are not capable of perfectly forecasting them.

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

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[13]I have also confirmed the robustness of the results along the following other dimensions: *i*) different lag specifications in the VAR; *ii*) alternative long-run contribution thresholds of the two identified shocks to RPI variation; *iii*) various correction thresholds of expectations in the boom-bust restriction; and *iv*) different choices for starting dates of the late 1990s boom period in the boom-bust restriction. These results are available upon request from the author.

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 Bernanke et al. (2005) data set (which updated the series used in Stock and Watson (1999) and Stock and Watson (2002)), as updated and used by Boivin et al. (2009). This data set contains a total of 111 various monthly macroeconomic indicators, which include several measures of industrial production, employment, various price indices, interest rates, stock prices, and other key macroeconomic and financial variables, all of which have been transformed to induce stationarity. The series span the period 1976:M2-2005:M6. I transform the computed principal components to quarterly frequency by averaging over the respective monthly values.

I ran two statistical exercises to eliminate the concern that non-invertibility is a major issue in my empirical analysis. First, consistent with the invertibility test proposed and used in Forni and Gambetti (2014) and Forni et al. (2014), Table 1 reports the p-values of the F-test of the regression of the median IST news shock series on four lags of the first n principal components, where n goes from 1 to 9. I truncate n at 9 as the first nine principal components explain about two thirds of the total variance of the Bernanke et al. (2005) data set. In all specifications the null of invertibility cannot be rejected at the 10% level clearly indicating that the identified IST news shock passes the invertibility test.

Second, as a complementary exercise, I also computed the correlations of the 1635 identified IST news shock series with the lagged values of the first nine principal components so as to learn more about the magnitude of their relation. These results are summarized in Figure 5, which presents the median and 10th and 90th percentiles of the correlations of my identified news shock with four lags of the first nine principal components. The results are conclusive: all correlations are small and largely insignificant, with all median correlations below 12% in absolute value and the 90th and 10th percentile correlations never exceeding 20% in absolute value. Thus, I can conclude that, in addition to formally passing the Forni and Gambetti (2014) invertibility test, my identified IST

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news shock also has a negligible correlation with all lagged principal components. Taken together, the results from both exercises are encouraging in that they imply that we can be fairly confident that the results of this paper are not driven by non-invertibility given that the benchmark VAR does not seem to suffer from informational deficiency.[14]

4.2   Relation between News Shocks and Stock Prices

Given the type of shock that is identified in this paper 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 benchmark VAR. If the identified shock were truly an IST news shock, then we should expect to see a significant impact response of stock prices to this shock. To examine this conjecture, I add to the benchmark VAR the log of the real S&P 500 Index, obtained from Robert Shiller's website, in per capita terms. This series is converted to a quarterly frequency by taking the last monthly observation from each quarter.

Figures 6a and 6b correspond to Figures 3a and 3b with the only difference being that now the benchmark VAR is replaced by a larger VAR that includes stock prices,[15] which enter the VAR in log-first-difference form. The figures are based on 10^6 randomly generated models from which a total of 181 admissible models were collected. Similar to the benchmark case (Figures 3a and 3b), favorable IST news shocks raise the real aggregates on impact and drive the bulk of their business cycle variation. In particular, the median contribution of IST news shocks to the two year variation in output, hours, investment, and consumption are 56%, 52%, 51%, and 55%, respectively. The news shocks also continue to raise interest rates and reduce inflation.

Interestingly, IST news shocks are also important drivers of the variation in stock prices, with a median contribution of 34% to their variation on impact, confirming the view that stock prices

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[14]To remove the concern that the invertibility test results are potentially affected by the sample period of the principal components being smaller that that of the benchmark VAR, I confirmed that the results remain unchanged when the news shocks are identified from the smaller sample period 1976:Q1-2005:Q2, i.e., the same sample as that of the estimated principal components.

[15]In the interest of space, the histogram figures that correspond to Figures 3a and 3b will not be presented in the robustness section. These figures are available upon request from the author.

contain valuable information about the future value of IST. This median contribution reflects a very significant median impact effect of 4.3% of IST news on stock prices. Furthermore, the contribution of the news shock to the variation in stock prices after the impact horizon is quite similar to the impact horizon contribution, indicating that stock prices mostly respond to news on impact; this result is consistent with the notion that stock prices reflect current available economic information and adjust instantaneously upon arrival of new information on future IST.

4.3   Results for a 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, in this section results from applying my methodology on a post 1982 sub-sample will be presented where it will be demonstrated that the sub-sample results, which are much less likely to suffer from potential heteroskedasticity and coefficient instability (e.g., Stock and Watson (2007)), are essentially the same as the large sample results.

Figures 7a and 7b correspond to Figures 3a and 3b with the only difference being that the former figures are based on a post 1982 sub sample (1983Q1-2012Q1). The figures are based on 10^6 randomly generated models from which a total of 445 admissible models were gathered. It is apparent the main results are unchanged for the sub sample period: IST news shocks drive the bulk of the business cycle variations in the real aggregates as well as the long-run variation in RPI, output, and consumption, and continue to generate business cycle comovement, raise interest rates, and lower inflation. The median contributions of IST news shocks to output, hours, investment, and consumption at the two year horizon are 68%, 57%, 58%, and 64%, respectively. Moreover, the median contributions to the long-run variation in RPI, output, and consumption are 71%, 66%, and 63%, respectively, emphasizing the importance of IST news shocks as drivers of not only the business cycle variation of the real aggregates but also the long-run movement in RPI, output, and consumption.

4.4 Non-Stationarity of Hours

The results of the previous section were obtained from a VAR in which hours were assumed to be stationary and thus entered the system in levels form. To test the robustness of the results to this assumption, I implemented the same identification procedure on a VAR in which hours are assumed to be non-stationary and thus enter the system in log-first-difference form. Figures 8a and 8b correspond to Figures 3a and 3b with the only difference being the latter modification. The figures are based on 10^6 randomly generated models from which a total of 291 admissible models were gathered.

It is apparent from the figures that the results of this paper are generally robust to the way that hours enter the system. IST news shocks continue to generate business cycle comovement as the real aggregates all rise significantly on impact in response to the news shock. The positive response of interest rates as well as the negative response of inflation are also maintained. Moreover, IST news shocks continue to drive a major share of the business cycle variation in the real aggregates with a 52% median contribution to output and consumption variation and a 43% contribution to investment and hours variation.

As Figure 8a illustrates, the response of hours to the IST news shock is permanent. While the assumption that hours are non-stationarity cannot be entirely ruled out on theoretical grounds, it is still hard to justify such a permanent response based on macroeconomic theory. Hence, imposing a first difference form on the log of hours may seem to be too restrictive. Nevertheless, the results from this section show that in general the main features of the results remain unchanged and are quite robust to the specification of hours in the VAR.

4.5 Relation between News Shocks and Credit Spreads

Recent work by Justiniano et al. (2011) has argued that there is a close relation between shocks to IST and shocks to financial intermediation as financial intermediation can potentially affect the production of capital goods. Justiniano et al. (2011) demonstrated that the IST shock estimated from their structural model has a strong correlation with credit spreads. In order to try to asses the

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relation between my identified news shocks and credit spreads, I apply the identification procedure on a VAR that includes the spread between the expected return on medium-grade bonds and high-grade bonds (Moody's seasoned Baa corporate bond yield and Aaa corporate bond yield, respectively). The monthly spread series is converted to a quarterly frequency by taking the last monthly observation from each quarter.

Figures 9a and 9b correspond to Figures 3a and 3b with the only difference being that the former are obtained from a VAR in which the credit spread variable is included. The figures are based on 10^6 randomly generated models from which a total of 789 admissible models were gathered. It is apparent from the figures that the results remain unchanged with respect to the benchmark results. IST news shocks continue to generate business cycle comovement, raise interest rates, lower inflation, and to drive the majority of the business cycle variations of the real aggregates (a median share of 59%, 62%, 53%, 55% of the two year variation in output, hours, investment, and consumption, respectively).

As for the implications for the credit spread variable, it is apparent that a financial accelerator mechanism is present following the news shock: the spread follows a hump shaped response, barely moving on impact and then starting to decline until peaking after 5 quarters. Moreover, the median contribution of the news shock to the two year variation in the spread is 13% while it explains less than 3% of its impact variation. The negligible impact median response of the spread is consistent with the very low median correlation of 9% between the identified news shocks and the VAR innovation in the spread. Given that the latter spread shock can be viewed as a shock to the functioning of credit markets, this low correlation can be seen as an indication that the results of this paper are not driven by credit supply disturbances.

4.6 Relation between News Shocks and TFP

Authors such as Beaudry and Portier (2004) and Karnizova (2012) view the news shocks that took place in the late 1990s as being strongly related to the expectations about the future expected gains from using the new and improved IT goods. This view implies that the late 1990s news shocks

portended a future increase in measured TFP and can therefore be interpreted as TFP news shocks. To examine whether such an interpretation is plausible, I apply my identification procedure on a VAR that includes a measure of TFP. 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 (2012).

Figures 10a and 10b correspond to Figures 3a and 3b with the only difference being that the former are obtained from a VAR in which TFP is included. The figures are based on 10^6 randomly generated models from which a total of 495 admissible models were gathered. It is apparent from the figures that the results remain unchanged with respect to the benchmark results and that the identified IST news shocks have a small and insignificant median effect on TFP at all horizons. This result implies that the IST news shocks identified in this paper are not related to TFP news shocks, thus suggesting that the TFP news-view of this period is misguided. More generally, this result suggests that the identified IST news shocks are not related to any type of TFP shock, be it anticipated or unanticipated TFP shocks.

One potential concern that can still arise is that the TFP news view of the boom-bust period is being rejected as a result of the presumption that the IST news view of this period is correct. To address this issue, I restricted the identified shock to be a non-IST shock, i.e., I only considered models in which the shock which complies with the boom-bust restriction does not have a long-run effect on RPI.[16],[17] The results from this exercise are presented in Figures 11a and 11b, which present the impulse responses and forecast error variance contributions for the identified non-IST shock, respectively. The figures are based on 10^6 randomly generated models from which a total of 14 admissible models were collected.

The results of this exercise deliver a conclusive message: the non-IST boom-bust shock has a

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[16]Operationally, the identified shock was restricted to have a long-run effect on RPI whose absolute value is smaller than 0.25%. The results are insensitive to other various smaller thresholds. Specifically, out of a total number of 14 admissible models, the absolute value of the RPI long-run response to the shock was smaller than 0.15% in 11 models while being larger than 0.2% in only one model, resulting in a median long-run response of less than 0.1%.

[17]Note that I am not identifying a structural shock here, but rather am letting the data speak as to the plausibility of a TFP news view of the boom-bust period. Specifically, if the non-IST shock is strongly related to TFP in a delayed manner this would suggest that the TFP news view is supported by the data.

small and insignificant effect on TFP at all horizons. This outcome emphasizes that the improbability of the TFP news view of the boom-bust period is robust to the assumption that the IST news view of this period is valid.

4.7 Alternative RPI Measure

While the GCV investment deflators are usually preferred to NIPA investment deflators as measures of RPI in the literature, it still seems worthwhile to check the robustness of my results to using the NIPA investment deflators for the RPI measure.[18] Figures 12a and 12b correspond to Figures 3a and 3b with the only difference being that the former are obtained from a VAR in which RPI is measured by the NIPA investment deflators rather than the GCV deflators. The figures are based on 10^6 randomly generated models from which a total of 891 admissible models were collected.

It is apparent from the figures that the results remain unchanged with respect to the benchmark results. IST news shocks continue to generate business cycle comovement, raise interest rates, lower inflation, and to drive the majority of the business cycle variation in the real aggregates (a median share of 63%, 66%, 60%, and 56% of the two year variations in output, hours, investment, and consumption, respectively). Moreover, the bulk of the long-run variation in RPI is accounted for by the news shock with a median contribution of 73%.

4.8 Cross-Correlations with Other Structural Disturbances

An additional concern that may arise from the benchmark results is that the identified IST news shock is correlated with other structural disturbances. To address this concern, I compute the correlation between the identified IST news shock and up to four lags and leads of the Romer and Romer (2004) monetary policy shock measure; the Romer and Romer (2010) tax shock measure; the shock to the real price of oil; the Ramey (2011) defense spending news shock measure; the TFP news shock from Barsky and Sims (2011); and the shock to the uncertainty measure used in Bloom

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[18]I also verified that the results are unchanged when the output deflator is used instead of the consumption deflator.

(2009), which is based on stock market volatility and corresponds to Figure 1 in his paper. Apart from the Barsky and Sims (2011) TFP news shock series which was used in its raw form, all other shocks were constructed as the residuals of univariate regressions of each of the five variables on its own four lags.

The results are presented in Figure 13, where the median and 10th and 90th percentiles of the correlations between the IST news shocks and up to four lags and leads of each of the other six disturbances are shown. The results indicate that the cross-correlations are small, with all median correlations lower than 16% in absolute value. Thus, it can be deduced that the main results of the paper are not driven by other structural disturbances.

5   Discussion

A better understanding of business cycles naturally requires a better knowledge of their sources. This paper has contributed to this understanding by providing robust evidence that IST news shocks constitute the major source of business cycles. Nevertheless, a consumer of these results might rightly argue that more information is needed on the nature of these news shocks, and more specifically, what real-life events they represent and originate from. This type of information can go a long way towards improving our understanding of economic fluctuations and towards enabling policy makers to better address these fluctuations, e.g., by allowing the detection of a potential beginning of an expansionary cycle given some large positive technological news event that is taking place.

In general, technology news shocks are unobserved and are thus hard to link to particular corresponding news events. While Ramey (2011) and Mertens and Ravn (2012) were able to use the narrative approach to construct series of defense spending and tax news shocks, respectively, an analogues narrative approach to technology news shocks is very hard to apply for three main reasons. First, it is difficult to quantify anticipated technological innovations given the general lack of quantitative information on their expected gains. Second, determining the exact timing of the

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arrival of information into economic agents' information sets is very hard to do. Last, but not least, it is an intricate task to handle negative news shocks, as these are likely to correspond to downward revisions of expectations that are probably hard to attach to real-life news events. It is thus not surprising that the technology news shocks literature has not applied the narrative approach to identifying news shocks. However, it is still possible to shed some light on the nature of the news shocks identified in this paper by focusing on the unique late 1990s period.

In particular, I focus on the semiconductor industry given its pivotal technological role as a driver of ICT (see, e.g., Aizcorbe et al. (2007) and references therein). According to Constable and Somerville (2003), two of the greatest technological innovations in the field of electronics in the 20th century, out of twenty overall, are the inventions of copper-based chip technology and plastic transistor technology, both of which are related to semiconductor manufacturing techniques and were announced in the late 1990s boom period.[19] The former invention was announced by IBM in September 1997 whereas the latter one was announced in March 1998 by a team of Bell Labs researchers. Both inventions experienced a delay between their introduction date and adoption date; copper-based chips were commercially available only in September 1998, a year after the initial announcement, while plastic transistors began to be commercially available in April 2002, i.e., with a much longer delay of four years.

Hence, these two breakthrough innovations constitute prominent examples of technological innovations that were anticipated in advance. By no means are they exceptional in this regard: my historical reading of other semiconductor innovations indicates that quite often these kinds of technological innovations were well anticipated in advance as information on them usually arrived prior to their commercial adoption. Moreover, information on the expected future time of commercial adoption was usually available. Interestingly, two of the three largest median realizations of my

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[19]This book is based on a comprehensive study conducted by the National Academy of Engineering (NAE), in collaboration with the American Association of Engineering Societies and National Engineers Week, aimed at determining the greatest engineering achievements in the 20th century in twenty different fields. The selection process was based on solicited nominations from members of 60 professional engineering societies from which the final greatest innovations were selected by an NAE committee consisting of renowned experts, where the chief criterion for nominations was the impact of the engineering achievement on quality of life.

identified IST news shocks series in the 1997-1999 period took place in the third quarter of 1997 and first quarter of 1998, with the former being the largest realization at 1.6 standard deviations and the latter being the third largest realization at 1.22 standard deviations. The correspondence between the large relative magnitude of the identified news shocks and the timing of the announcements of the inventions is an indication that, at least to some extent, these large news shocks represent the significant news events triggered by the two inventions.

6 Conclusion

This paper has provided robust evidence that IST news shocks are the main force behind business cycle fluctuations, reduce inflation, and raise nominal interest rates. To obtain these results, I applied a novel identification approach that exploits the view that the late 1990s early 2000s boom-bust period can be characterized as an IST news-driven episode and identified an IST news shock as the shock that i) has a long-run effect on RPI and ii) has its maximal three-year moving average of realizations in the boom period, followed by a negative average in the bust period.

The results of this paper on the business cycle implications of IST news shocks, at least in terms of the ability of the latter shocks to generate business cycle comovement, can be explained by modern macroeconomic theory. An IST news-driven DSGE model that contains the Jaimovich and Rebelo (2009) preference structure, investment adjustment costs, and endogenous capital utilization can, in general, generate the empirical impulse responses obtained in this paper. Nevertheless, these impulse responses are not robust to different parameterizations as employing the calibration used in Jaimovich and Rebelo (2009) generates business cycle driving IST news shocks while using the estimated parameters obtained in Khan and Tsoukalas (2011) does not deliver similar impulse responses.

Hence, it may be suitable to consider developing more robust models along the lines of the recent paper by Dupor and Mekhari (2011) in which investment is forward-compatible in the sense that it rises in response to IST news so that by the time the technology arrives the complementary

capital is already in place. This kind of mechanism is appealing as it is consistent with what we observed during the late 1990s when investment surged in anticipation of ICT improvement. One prominent example of this mechanism, as noted by Dupor and Mekhari (2011), is the considerable rise in investment in fiber optic cables in the late 1990s in anticipation of future ICT improvements. This mechanism is also in agreement with the results of this paper as identified favorable IST news shocks generate a significant contemporaneous expansion in investment.

References

Aizcorbe, A., Flamm, K. and Khurshid, A.: 2007, The role of semiconductor inputs in it hardware price decline: Computers versus communications, *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches*, NBER Chapters, National Bureau of Economic Research, Inc, pp. 351–381.

Arias, J., Rubio-Ramirez, J. F. and Waggoner, D. F.: 2014, Inference based on svars identified with sign and zero restrictions: Theory and applications.

Barsky, R. and Sims, E.: 2011, News shocks and business cycles, *Journal of Monetary Economics* **58**(3), 235–249.

Barsky, R. and Sims, E.: 2012, Information, animal spirits, and the meaning of innovations in consumer confidence, *American Economic Review* **102**(4), 1343–1377.

Basu, S., Fernald, J., Fisher, J. and Kimball, M.: 2010, Sector-specific technical change, *Manuscript*, Boston College.

Beaudry, P. and Lucke, B.: 2010, Letting different views about business cycles compete, *in* K. Rogoff and M. Woodford (eds), *NBER Macroeconomics Annual*, Vol. 24, University of Chicago Press, pp. 413–455.

Beaudry, P., Nam, D. and Wang, J.: 2011, Do mood swings drive business cycles and is it rational?, *Working Paper 17651*, NBER.

Beaudry, P. and Portier, F.: 2004, An exploration into pigou's theory of cycles, *Journal of Monetary Economics* **51**(6), 1183–1216.

Ben Zeev, N. and Khan, H.: 2015, Investment-Specific News Shocks and U.S. Business Cycles, *Journal of Money, Credit and Banking (forthcoming)* .

Bernanke, B., Boivin, J. and Eliasz, P. S.: 2005, Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach, *The Quarterly Journal of Economics* **120**(1), 387–422.

Bloom, N.: 2009, The impact of uncertainty shocks, *Econometrica* **77**(3), 623–685.

Boivin, J., Giannoni, M. P. and Mihov, I.: 2009, Sticky prices and monetary policy: Evidence from disaggregated us data, *American Economic Review* **99**(1), 350–84.

Canova, F. and De Nicolo, G.: 2002, Monetary disturbances matter for business fluctuations in the G7, *Journal of Monetary Economics* **49**(6), 1131–1159.

Canova, F., Lopez-Salido, D. and Michelacci, C.: 2010, The effects of technology shocks on hours and output: A robustness analysis, *Journal of Applied Econometrics* **25**(5), 755–773.

Constable, G. and Somerville, B.: 2003, *A Century of Innovation: The Engineering That Transformed Our Lives*, National Academies Press.

Cummins, J. and Violante, G.: 2002, Investment-specific technical change in the US (1947-2000), *Review of Economic Dynamics* **5**(2), 243–284.

Dedola, L. and Neri, S.: 2007, What does a technology shock do? a VAR analysis with model-based sign restrictions, *Journal of Monetary Economics* **54**(2), 512–549.

Dupor, B. and Mekhari, M.: 2011, News shocks and forward-compatible investment, *Manuscript*, Ohio State University.

Fernald, J.: 2012, A quarterly utilization-adjusted series on total factor productivity, *Technical report*, Federal Reserve Bank of San Francisco.

Fernandez-Villaverde, J., Rubio-Ramirez, J., Sargent, T. and Watson, M.: 2007, ABCs (and Ds) for understanding VARs, *American Economic Review* **97**(3), 1021–1026.

Fisher, J.: 2006, The dynamic effects of neutral and investment-specific shocks, *Journal of Political Economy* **114**(3), 413–451.

Forni, M. and Gambetti, L.: 2014, Sufficient information in structural VARs, *Journal of Monetary Economics (forthcoming)* .

Forni, M., Gambetti, L. and Sala, L.: 2014, No news in business cycles, *The Economic Journal (forthcoming)* .

Gordon, R.: 1990, *The Measurement of Durable Goods Prices*, University of Chicago Press.

Greenwood, J., Hercowitz, Z. and Huffman, G.: 1988, Investment, capacity utilization and the real business cycle, *American Economic Review* **78**(3), 402–417.

Greenwood, J., Hercowitz, Z. and Krusell, P.: 1997, Long-run implications of investment-specific technical change, *American Economic Review* **87**(3), 342–362.

Greenwood, J., Hercowitz, Z. and Krusell, P.: 2000, The role of investment-specific technological change in the business cycle, *European Economic Review* **44**(1), 91–115.

Helbling, T., Huidrom, R., Kose, M. A. and Otrok, C.: 2011, Do credit shocks matter? A global perspective, *European Economic Review* **55**(3), 340–353.

Jaimovich, N. and Rebelo, S.: 2009, Can news about the future drive the business cycle?, *American Economic Review* **99**(4), 1097–1118.

Justiniano, A., Primiceri, G. and Tambalotti, A.: 2011, Investment shocks and the relative price of investment, *Review of Economic Dynamics* **14**(1), 101–121.

Karnizova, L.: 2012, News shocks, productivity and the U.S. investment boom-bust cycle, *The B.E. Journal of Macroeconomics* **12**(1), 1–50.

Khan, H. and Tsoukalas, J.: 2011, Investment shocks and the comovement problem, *Journal of Economic Dynamics and Control* **35**(1), 115–130.

Khan, H. and Tsoukalas, J.: 2012, The quantitative importance of news shocks in estimated DSGE models, *Journal of Money, Credit and Banking (forthcoming)* .

Kilian, L. and Murphy, D.: 2012, Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market VAR models, *Journal of the European Economic Association* **10**(5), 1166–1188.

Leeper, E. M., Walker, T. B. and Yang, S. S.: 2013, Fiscal foresight and information flows, *Econometrica* **81**(3), 1115–1145.

Leeper, E. and Walker, T.: 2011, Information flows and news driven business cycles, *Review of Economic Dynamics* **14**(1), 55–71.

Liu, Z., Waggoner, D. and Zha, T.: 2011, Sources of macroeconomic fluctuations: A regime-switching dsge approach, *Quantitative Economics* **2**(2).

Mertens, K. and Ravn, M. O.: 2012, Empirical evidence on the aggregate effects of anticipated and unanticipated us tax policy shocks, *American Economic Journal: Economic Policy* **4**(2), 145–81.

Mountford, A. and Uhlig, H.: 2009, What are the effects of fiscal policy shocks?, *Journal of Applied Econometrics* **24**(6), 960–992.

Peersman, G. and Straub, R.: 2009, Technology shocks and robust sign restrictions in a euro area SVAR, *International Economic Review* **50**(3), 727–750.

Ramey, V.: 2011, Identifying government spending shocks: It's all in the timing, *The Quarterly Journal of Economics* **126**(1), 1–50.

Romer, C. and Romer, D.: 2004, A new measure of monetary shocks: Derivation and implications, *American Economic Review* **94**(4), 1055–1084.

Romer, C. and Romer, D.: 2010, The macroeconomic effects of tax changes: Estimates based on a new measure of fiscal shocks, *American Economic Review* **100**(3), 763–801.

Rubio-Ramirez, J., Waggoner, D. and Zha, T.: 2010, Structural vector autoregressions: Theory for identification and algorithms for inference, *Review of Economic Studies* **77**(2), 665–696.

Schmitt-Grohé, S. and Uribe, M.: 2012, What's news in business cycle?, *Econometrica (forthcoming)* .

Sims, E.: 2012, News, non-invertibility, and structural VARs, *Advances in Econometrics (fortcoming)* .

Smets, F. and Wouters, R.: 2007, Shocks and frictions in the us business cycle: A bayesian dsge approach, *American Economic Review* **97**(3), 586–606.

Stock, J. H. and Watson, M. W.: 1999, Forecasting inflation, *Journal of Monetary Economics* **44**(2), 293 – 335.

Stock, J. H. and Watson, M. W.: 2002, Macroeconomic forecasting using diffusion indexes, *Journal of Business and Economic Statistics* **20**(2), 147–162.

Stock, J. and Watson, M.: 2007, Why has U.S. inflation become harder to forecast?, *Journal of Money, Credit and Banking* **39**(2), 3–33.

Uhlig, H.: 1994, What macroeconomists should know about unit roots: A bayesian perspective, *Econometric Theory* **10**(3/4), 645–671.

Uhlig, H.: 2005, What are the effects of monetary policy on output? evidence from an agnostic identification procedure, *Journal of Monetary Economics* **52**(2), 381–419.

Appendix A   Posterior Distribution of Reduced Form VAR Parameters

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

$$Y = XB + U \tag{6}$$

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:

$$vec(B) \mid \Sigma \quad \sim \quad N(vec(\bar{B}_0), \Sigma \otimes N_0^{-1}) \tag{7}$$

$$\Sigma \quad \sim \quad IW_k(v_0 S_0, v_0) \tag{8}$$

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:

$$vec(B) \mid \Sigma \quad \sim \quad N(vec(\bar{B}_T), \Sigma \otimes N_T^{-1}) \tag{9}$$

$$\Sigma \quad \sim \quad IW_k(v_T S_T, v_T) \tag{10}$$

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 $N_T = X'X$. Thus, the posterior simulator for B and Σ 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. Repeat steps 1 and 2 a large number of times and collect the drawn B's and Σ's.

Table 1: **F-Test of Regression of identified IST News Shock Series on Lagged Principal Components**

	Principal Components (from 1 to n)								
	1	2	3	4	5	6	7	8	9
P-Value	0.54	0.43	0.24	0.1	0.15	0.19	0.12	0.1	0.1

Notes: Column n reports the p-value of the F-test of the regression of the median IST news shocks series on four lags of the first n principle components extracted from the Bernanke et al. (2005) comprehensive data set, where n goes from 1 to 9.

Figure 1: **Shiller's Cyclically Adjusted Price-Earnings Ratio**.
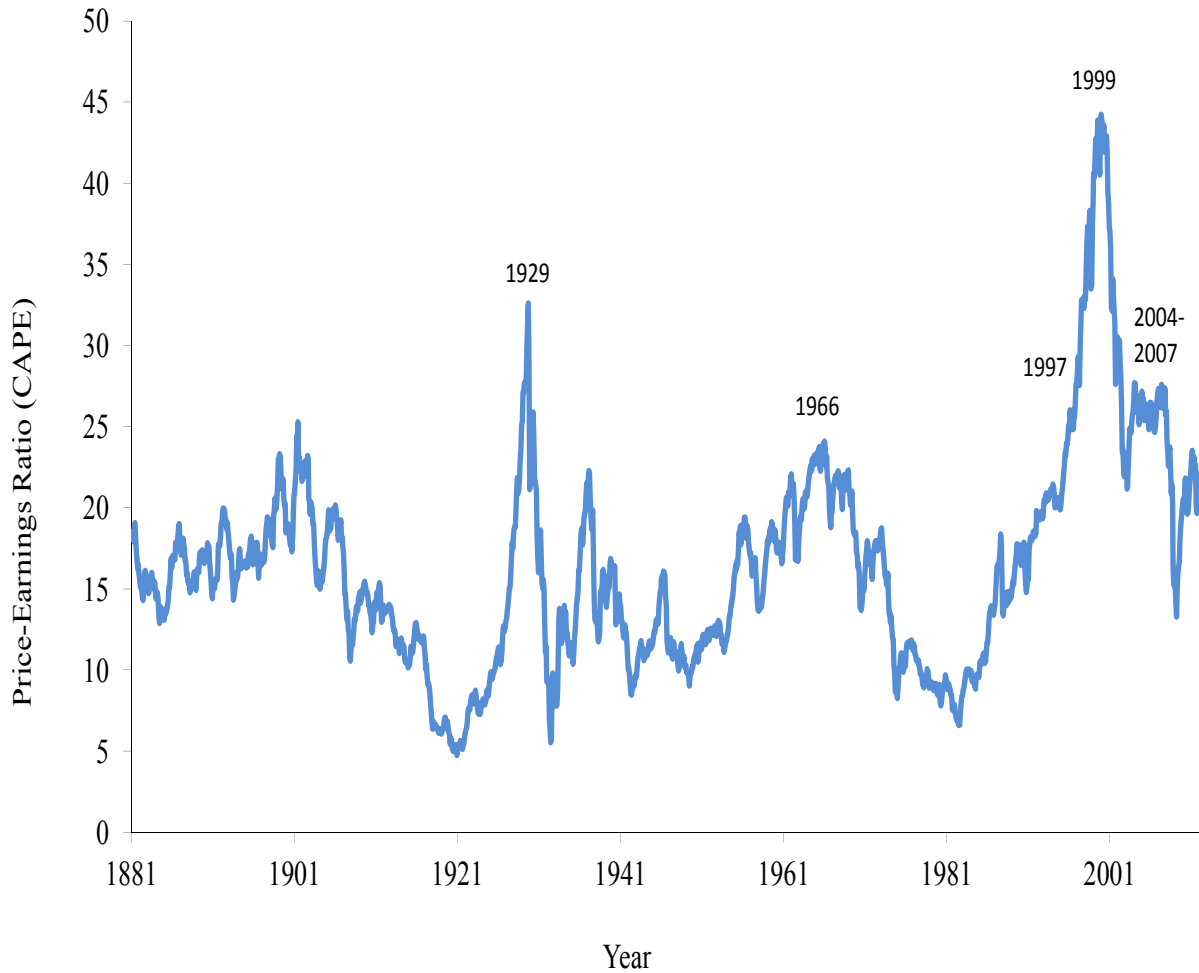
Notes: The figure shows the monthly Shiller's cyclically adjusted price-earnings ratio, defined as the ratio of the real S&P 500 and the trailing 10 year real S&P 500 earnings, for the period of 1881:M1-2012:M6.

Figure 2: Benchmark VAR: (a) Impact Response Histogram; (b) Two Year FEV Histogram
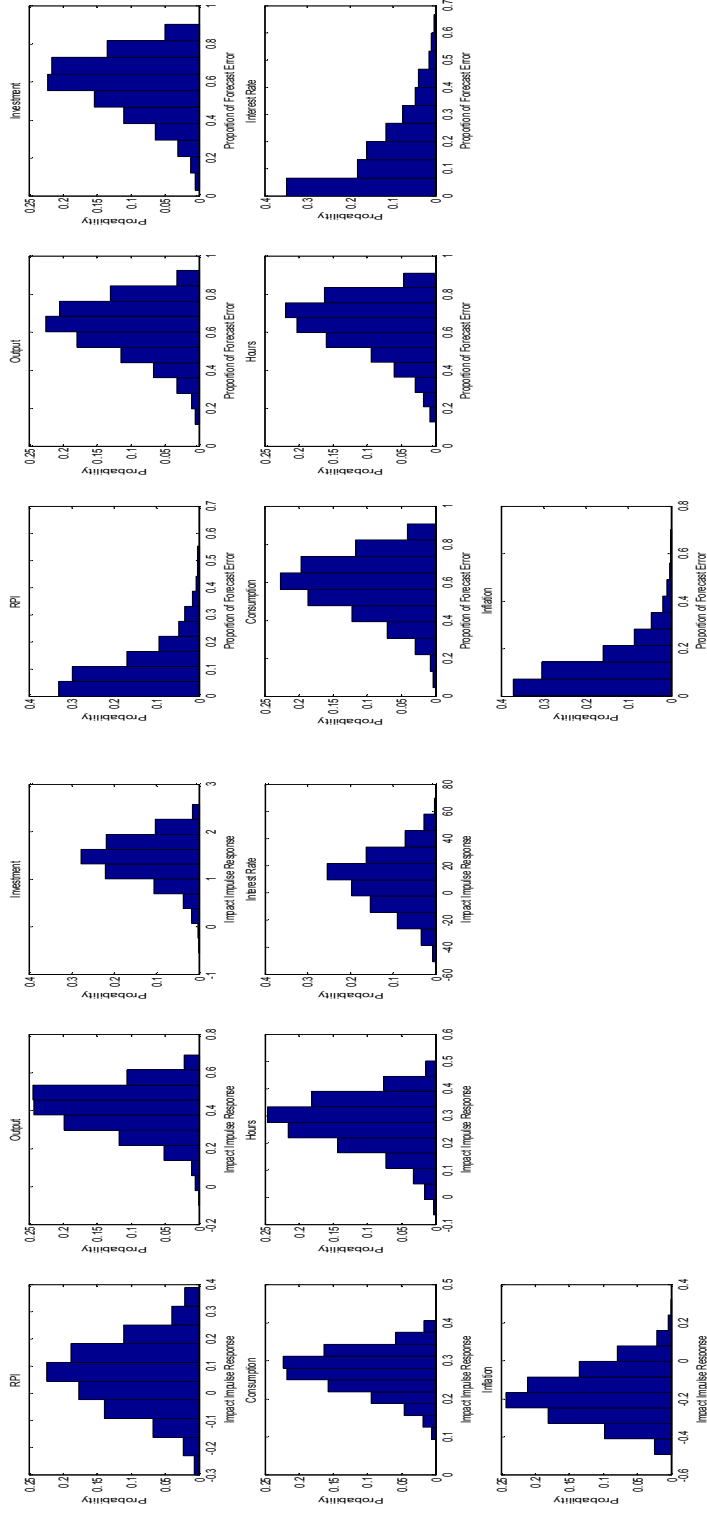
(a) **Normalized Histogram of Impact Impulse Responses to an IST News Shock.**

(b) **Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.**

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from the benchmark VAR). Panel (b): This figure presents the posterior distribution of the contribution of the IST news shock to the forecast error variance of the variables at the two year horizon (obtained from the benchmark VAR).

Figure 3: **Benchmark VAR: (a) Impulse Responses ; (b) Contribution to FEV**
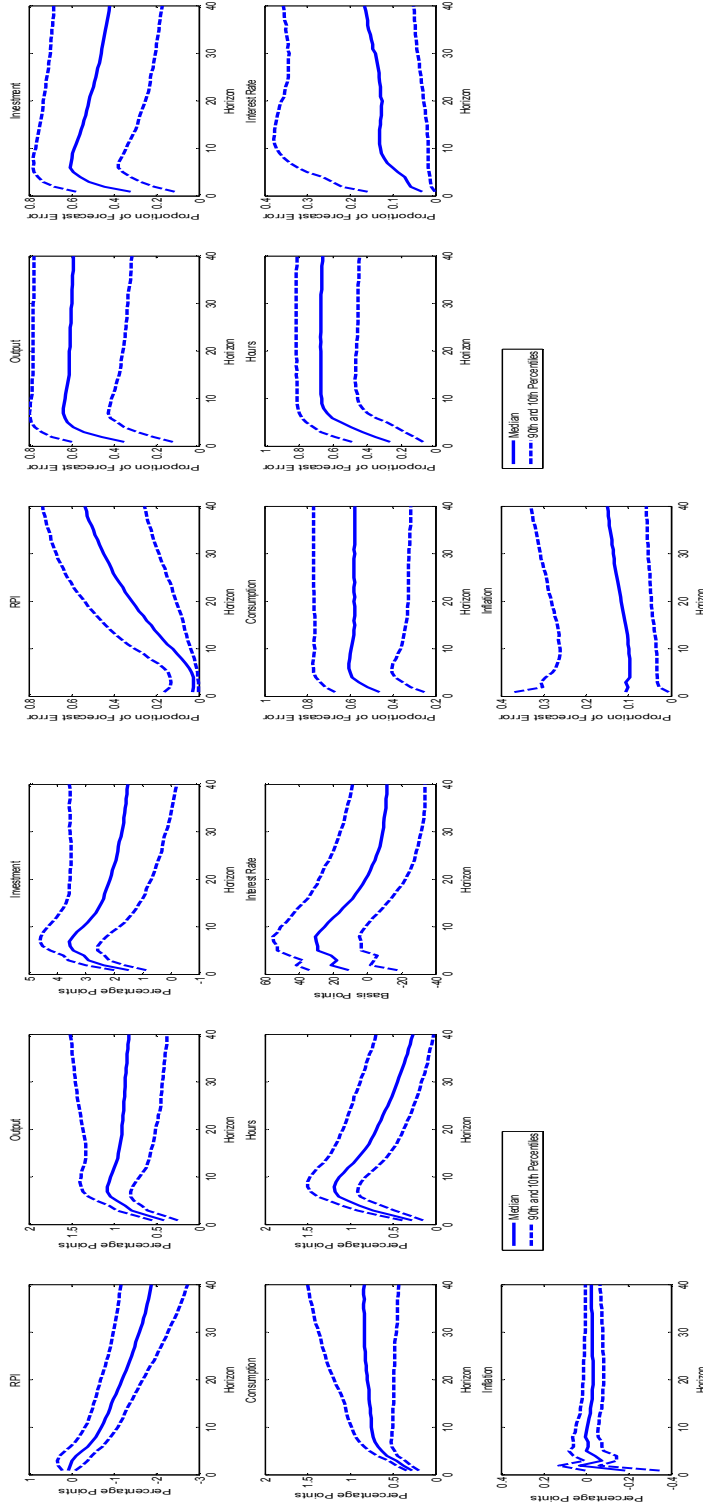
(a) **The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks.**

(b) **The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses (obtained from the benchmark VAR). Panel (b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions (obtained from the benchmark VAR).

Figure 4: **Identified IST News Shock Time Series (Smoothed) and U.S. Recessions.**
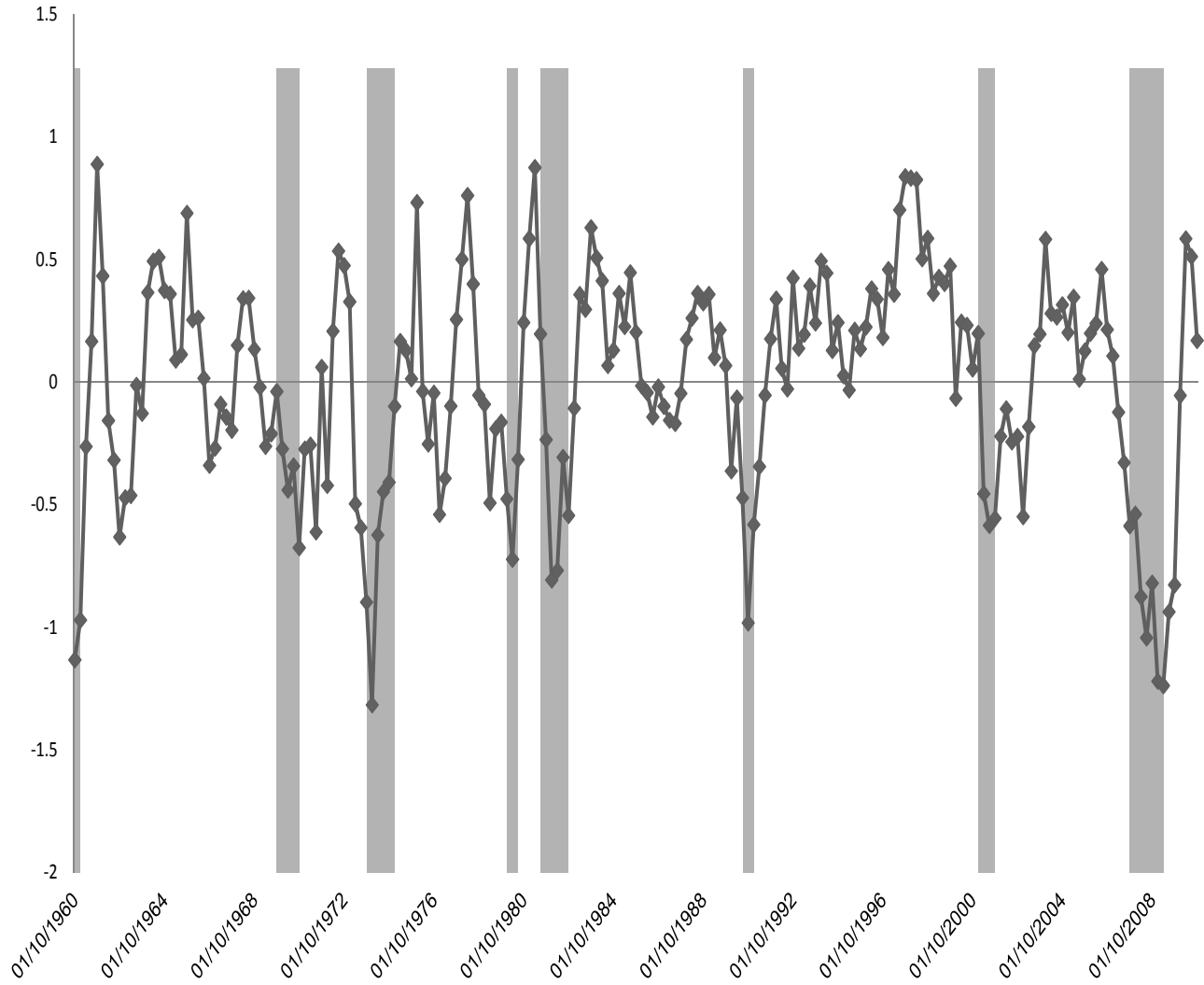
Notes: The U.S. recessions are represented by the shaded areas. To render the figure more readable, the plotted median identified shock series is smoothed using a one year moving average. Specifically, it is calculated as $\varepsilon_t^s = (\varepsilon_{t-3} + \varepsilon_{t-2} + \varepsilon_{t-1} + \varepsilon_t)/4$, where ε_t is the median of the 1635 identified shock series. The plotted series begins in 1960:Q4 and ends in 2012:Q1.

Figure 5: **The Median and 90th and 10th Percentiles of the Correlation between the IST News Shock and Lags of Principal Components**.
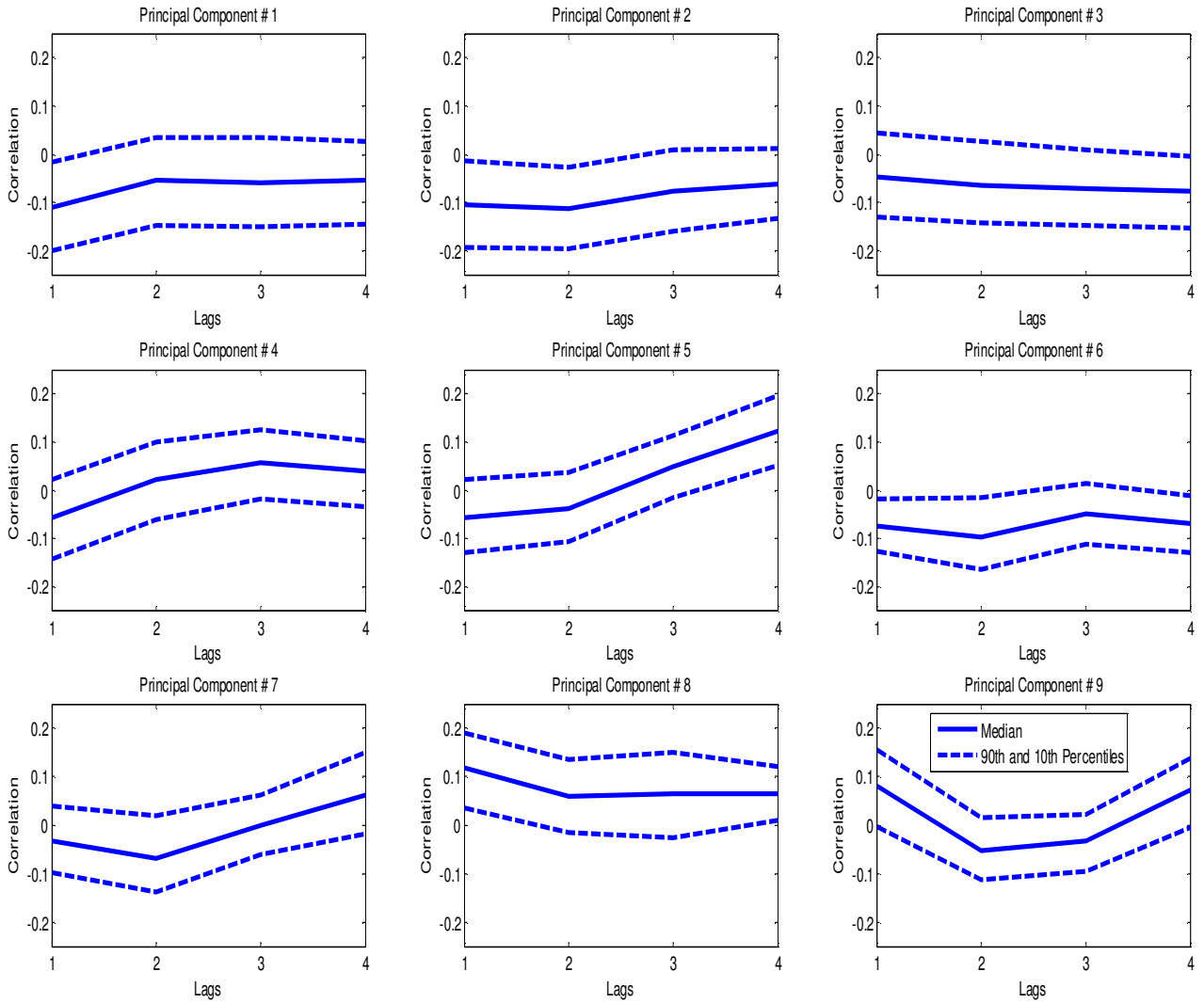
Notes: The solid line is the median correlation and the dashed lines are the 90th and 10th percentiles of the posterior distribution of correlations. The nine principle components are extracted from the Bernanke et al. (2005) comprehensive data set.
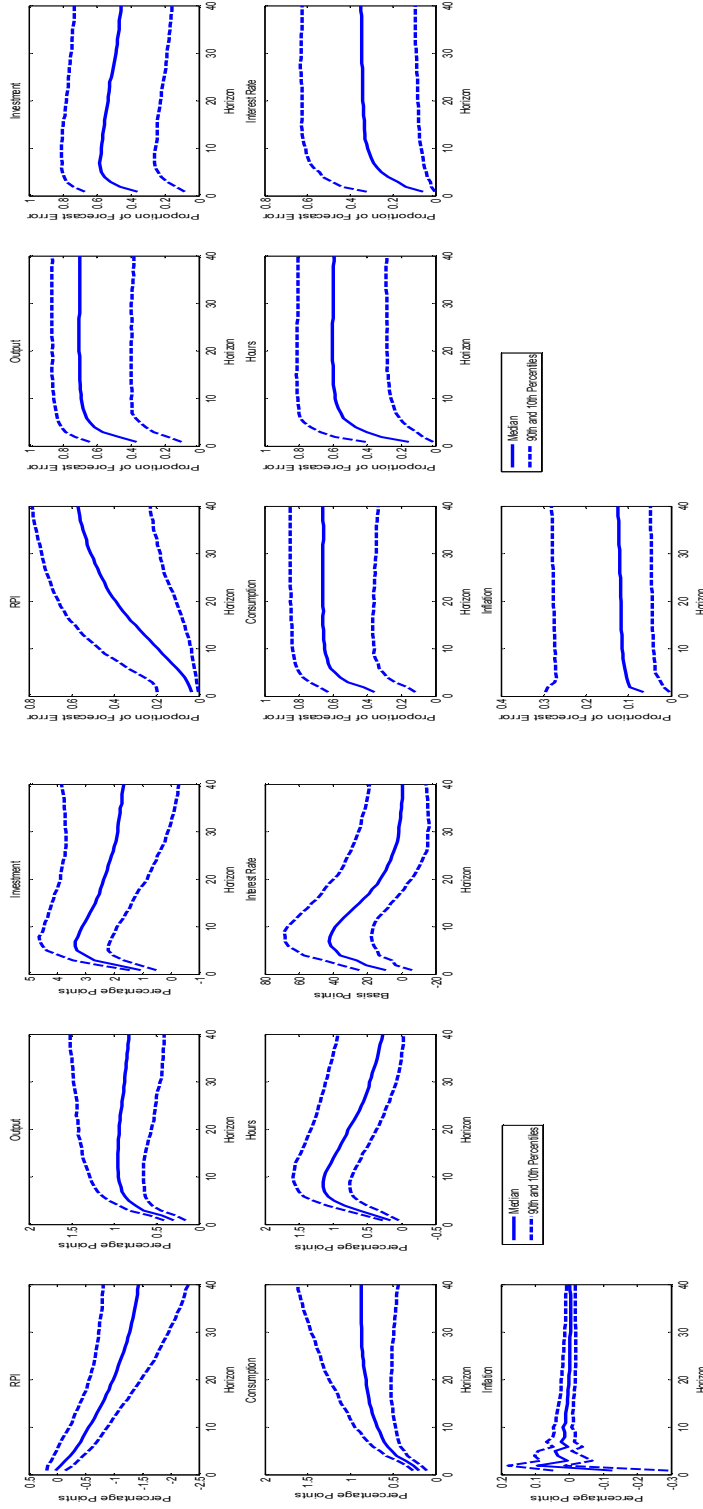
39

Figure 6: **VAR With Stock Prices: (a) Impulse Responses ; (b) Contribution to FEV**
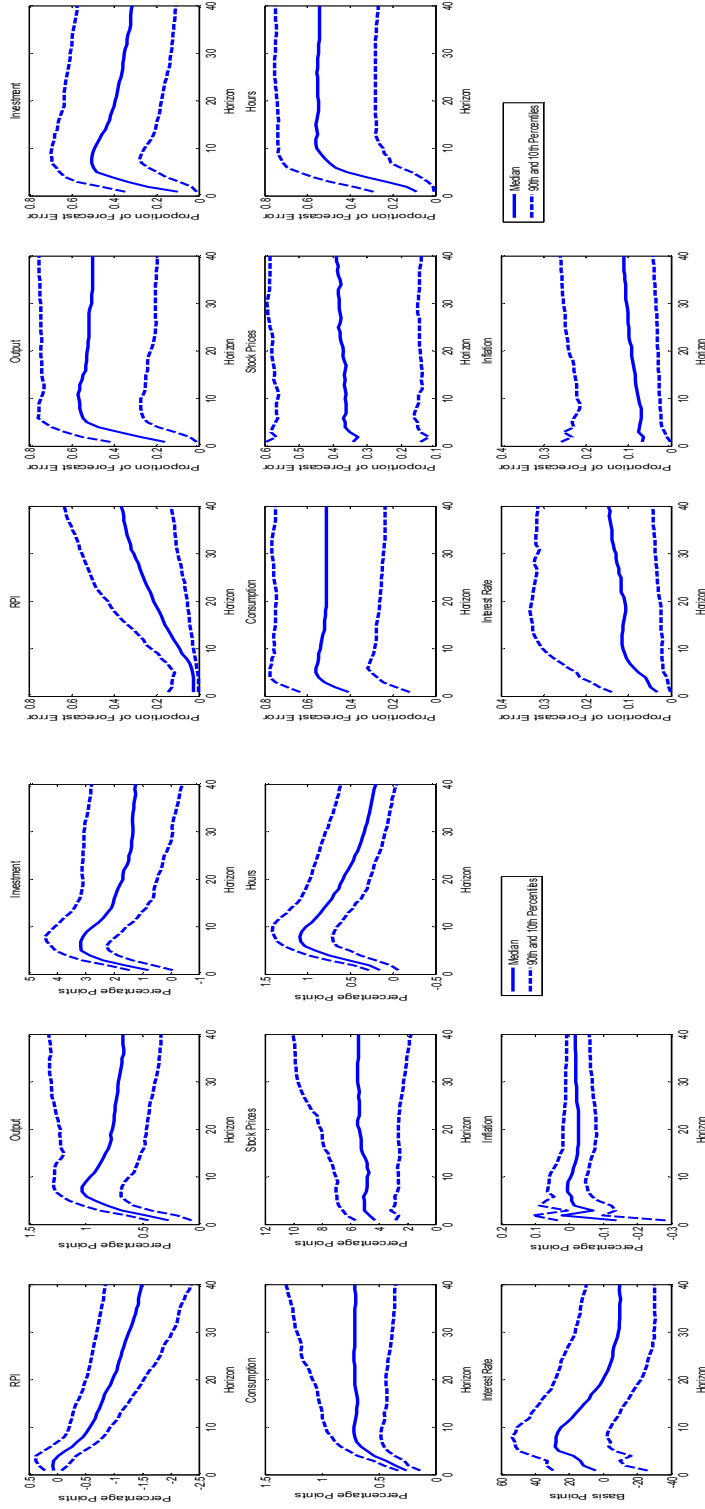
(a) **The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks.**

(b) **The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses (obtained from a VAR that includes stock prices). Panel (b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions (obtained from a VAR that includes stock prices).
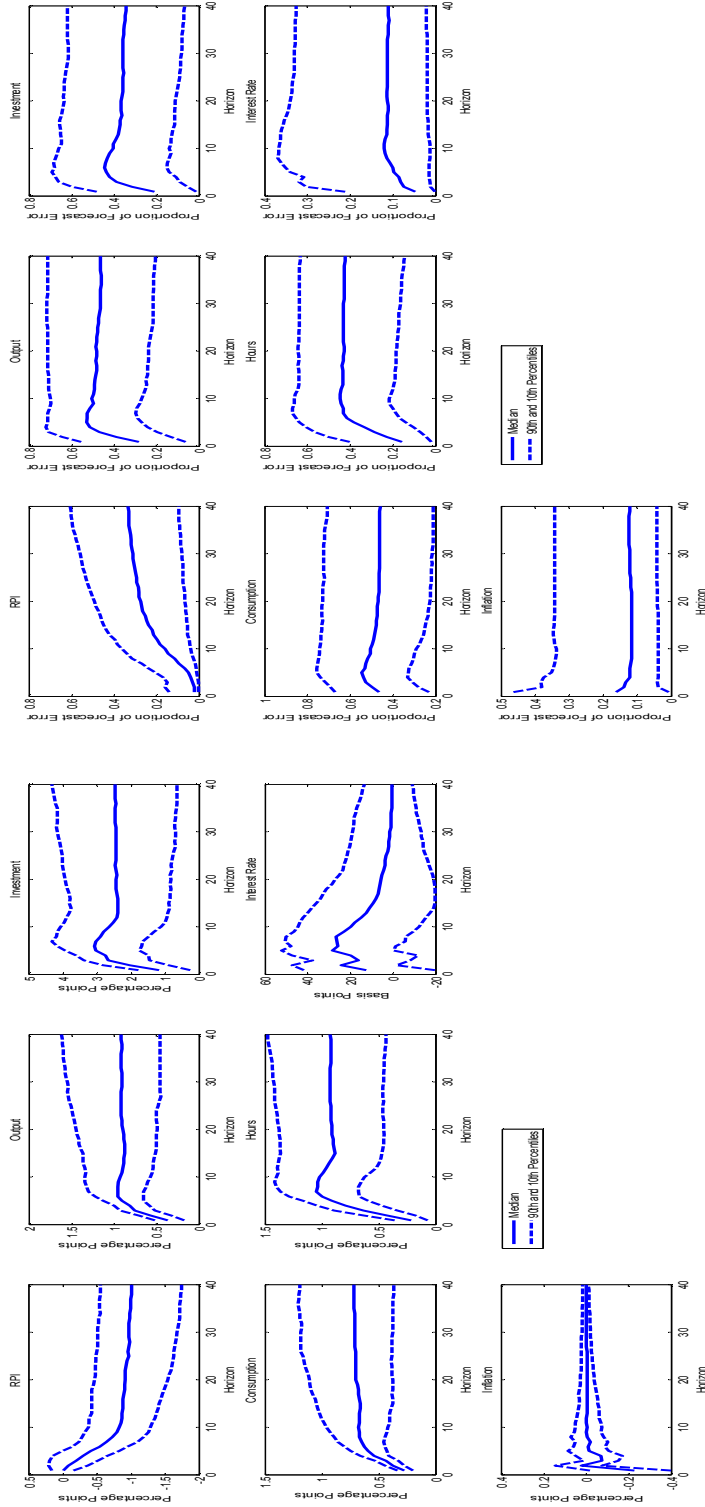
Figure 7: Post 1982 Sample: (a) Impulse Responses ; (b) Contribution to FEV

(a) The Median and 90th and 10th Percentiles of the Im-
pulse Responses to IST News Shocks.

(b) The Median and 90th and 10th Percentiles of the Con-
tribution of IST News Shock to Forecast Error Vari-
ance of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles
of the posterior distributions of impulse responses (obtained from a post 1982 sample). Panel (b): The solid line is the
median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions
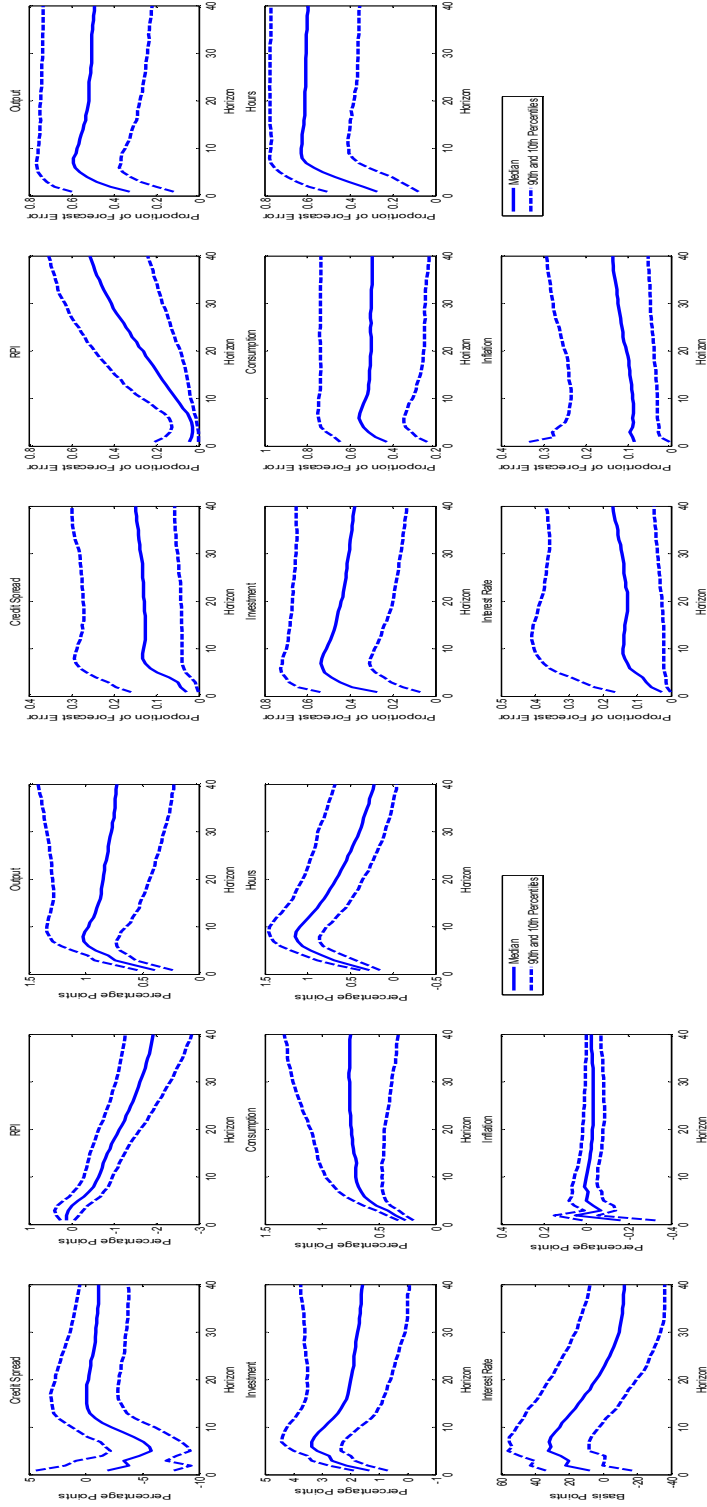(obtained from a post 1982 Sample).

Figure 8: **Non-Stationary Hours: (a) Impulse Responses ; (b) Contribution to FEV**

(a) **The Median and 90th and 10th Percentiles of the Impulse Responses to IST News Shocks.**

(b) **The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses (obtained from entering hours in VAR in log-first-difference form). Panel (b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions (obtained from entering hours in VAR in log-first-difference form).
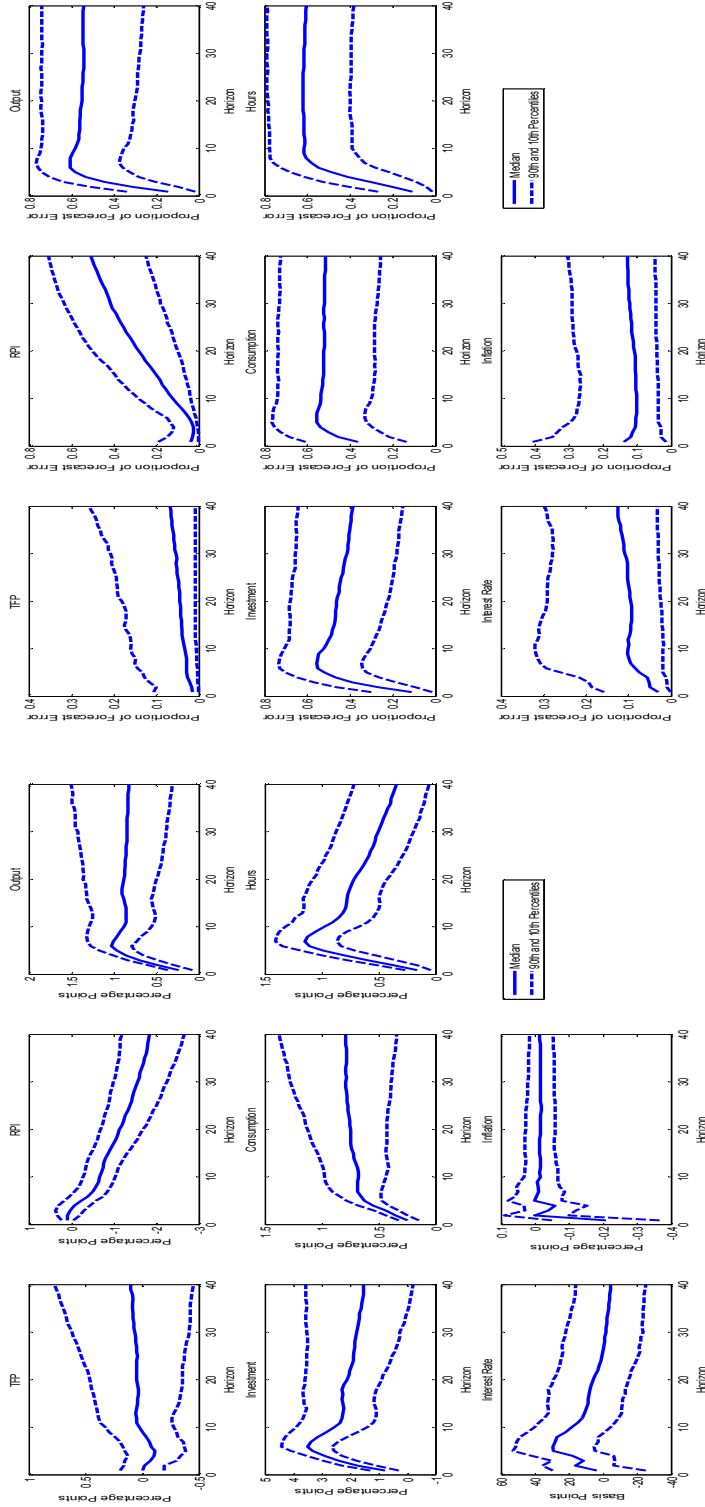
42

Figure 9: **VAR With Credit Spread: (a) Impulse Responses ; (b) Contribution to FEV**

(a) **The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks.**

(b) **The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses (obtained from a VAR that includes a credit spread variable). Panel (b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions (obtained from a VAR that includes a credit spread variable).
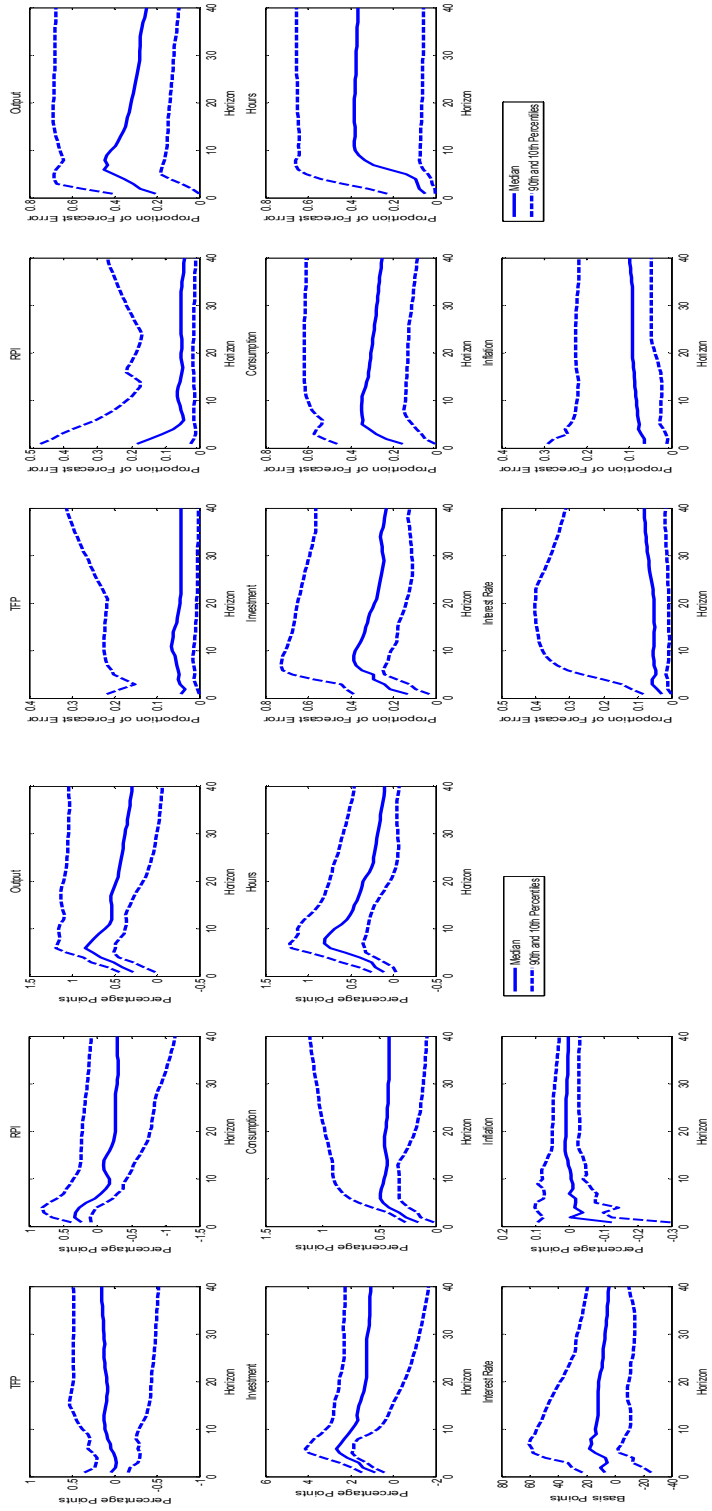
43

Figure 10: **VAR With TFP: (a) Impulse Responses ; (b) Contribution to FEV**

(a) **The Median and 90th and 10th percentiles of the Im-**
pulse Responses to IST News Shocks.

(b) **The Median and 90th and 10th Percentiles of the Con-**
tribution of IST News Shock to Forecast Error Vari-
ance of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles
of the posterior distributions of impulse responses (obtained from a VAR that includes TFP). Panel (b): The solid
line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of
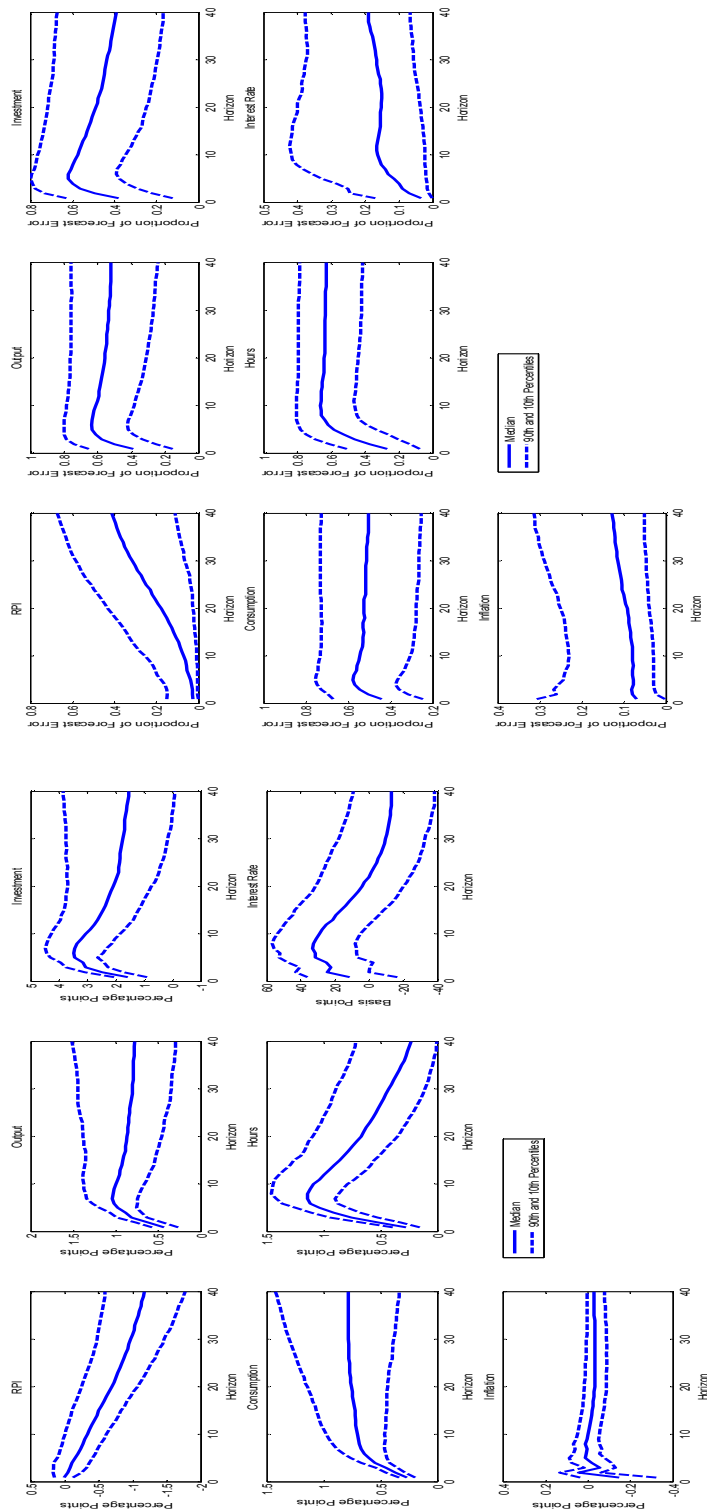contributions (obtained from a VAR that includes TFP).

Figure 11: **Non-IST Shock: (a) Impulse Responses ; (b) Contribution to FEV**

(a) **The Median and 90th and 10th percentiles of the Im-** (b) **The Median and 90th and 10th Percentiles of the Con-**
pulse Responses to the Non-IST Shocks. **tribution of the Non-IST Shock to Forecast Error Vari-**
ance of the Variables.

Notes: The shock identified in these figures is a shock that complies with the boom-bust restriction, i.e., experiences its
maximal sum of realizations in the boom period followed by at least a 25% correction in the bust period, but is restricted
to not be one of the two shocks driving the long-run variation in RPI. Panel (a): The solid line is the median impulse
response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses. Panel
(b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior
distribution of contributions.

Figure 12: **Alternative RPI Measure: (a) Impulse Responses ; (b) Contribution to FEV**

(a) **The Median and 90th and 10th percentiles of the Im- (b) The Median and 90th and 10th Percentiles of the Con-pulse Responses to IST News Shocks.**

tribution of IST News Shock to Forecast Error Variance of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses (obtained from a VAR in which RPI is measured using NIPA investment deflators). Panel (b): The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions (obtained from a VAR in which RPI is measured using NIPA investment deflators).

Figure 13: **The Median and 90th and 10th Percentiles of the Cross-Correlation between the IST News Shock and Lags/Leads of Other Shocks**.
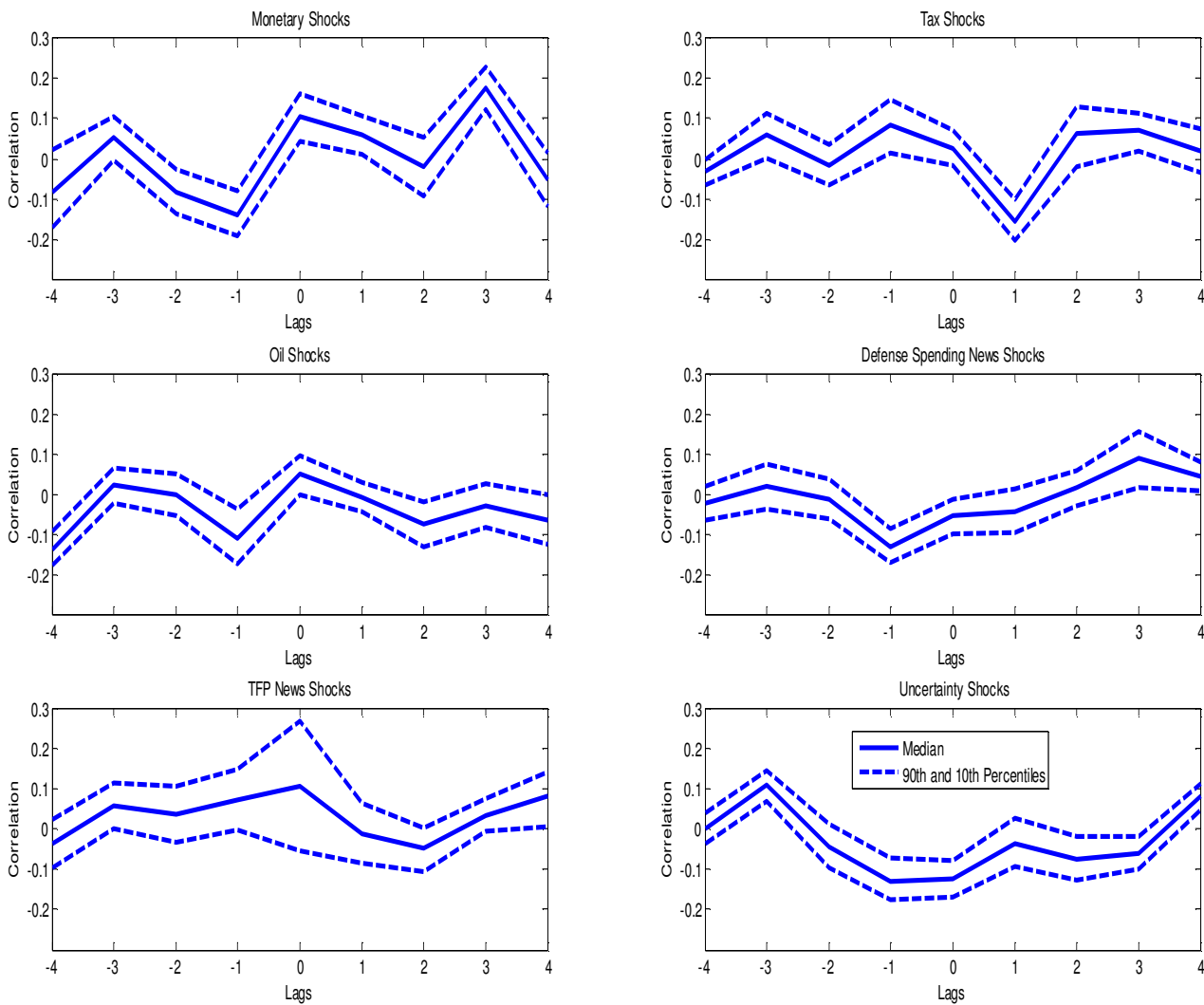
Notes: The solid line is the median cross-correlation and the dashed lines are the 90th and 10th percentiles of the posterior distribution of cross-correlations. The other shocks are the Romer and Romer (2004) monetary policy shock measure, Romer and Romer (2010) tax shock measure, shock to the real price of oil, the Ramey (2011) defense spending news shock measure, the TFP news shock from Barsky and Sims (2011), and the shock to the uncertainty measure used in Bloom (2009) which is based on stock market volatility and corresponds to Figure 1 in his paper. Apart from the Barsky and Sims (2011) TFP news shock series which was used in its raw form, all other shocks were constructed as the residuals of univariate regressions of each of the five variables on four lags.