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

Nadav Ben Zeev *
European University Institute
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Abstract

The boom-bust period of 1997-2003 is commonly viewed as an expectations-driven episode in which overly optimistic expectations about investment-specific technology (IST) were followed by their downward revision. I first demonstrate via a variety of VAR’s the robust result that the shock which has 1) a long-run effect on the relative price of investment and 2) the maximal moving average of realizations in the boom period and a negative average in the bust period is a shock that raises output, hours, investment, and consumption, and accounts for the majority of their business cycle variation. Using suitable Monte Carlo experiments, this paper shows that the latter result is very likely to have been generated by a model in which IST news shocks are the main force behind business cycles.

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Key words: Investment-specific technology, News shocks, Business cycles

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Contact details: Max Weber Programme, European University Institute, Villa la Fonte, Via delle Fontanelle 20, 50014
Tel.: [+39] 055 4685 603, Fax: [+39] 055 4685 804
E-mail: nadav.benzeev@eui.eu
1 Introduction

The 1997-2003 period was a significant boom-bust period in the U.S economy that is commonly viewed as an episode driven by overly optimistic expectations about investment-specific technology (IST) and the subsequent downward revision of these expectations (e.g. Beaudry and Portier (2004), Jaimovich and Rebelo (2009), and Karnizova (2012)).\(^1\) Figure 1 depicts some data that is indicative of this special episode. The figure shows the monthly Shiller’s cyclically adjusted price-earnings ratio (Henceforth: CAPE), 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. It is apparent that the 1997-1999 period was a period of extremely high CAPE levels as already in the beginning of 1997 the CAPE reached a level that exceeded the very high levels that prevailed during the period of 2006-2007. Then, from 1997 to the end of 1999 it kept rising until peaking at an all time high value of 44.2 in December of 1999, from which point it started to decline reaching a trough of 21.1 in February 2003.

I propose a novel identification approach that exploits this information on the 1997-2003 boom-bust period to identify IST news shocks by imposing on the identified news shock series to 1) have a long-run effect on the the relative price of investment (RPI) and 2) have its maximal three year moving sum in the 1997-1999 period followed by a negative sum in the bust period which is at least 25% in absolute value of the boom period sum.\(^2\) The restriction on the 1997:Q1-1999:Q4 sub-series imposes on the sum of shock realizations in the period 1997-1999 to be larger than any other three year period sum and manifests the view that this period is plausibly the most apparent IST

\(^{1}\)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 IST. Specifically, the expectations are thought to have been mostly related to information and communications technology (ICT), which is an important component of IST and has accounted for roughly one half of the overall investment in equipment and software since the late 1990’s.

\(^{2}\)Specifically, Under 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 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. Hence, as will be explained in the next section, I allow for an additional shock to have a long-run effect on RPI by imposing on 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.
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.\footnote{The results of this paper are insensitive to imposing different correction thresholds.}

I apply the identification strategy to a VAR that contains RPI, the real aggregates, inflation, and interest rates and find that the identified IST news shock raises output, hours, investment, and consumption, and accounts for the majority of their business cycle variation. Moreover, this shock raises interest rates, lowers inflation, and accounts for the bulk of the long-run variation in output 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). Then, utilizing suitable Monte Carlo experiments aimed at examining the reliability of the empirical results, I demonstrate that the empirical results produced by this paper are very likely to have been generated by a model in which IST news are the main force behind business cycles.

The Monte Carlo evidence in Section 5 shed light on the ability of the identification procedure used in this paper to recover the effects of the IST news shock and enables one to deduce that it is very likely that the true model is one which IST news shocks are the major force behind business cycle fluctuations. In particular, I find that when IST news shocks are the main force behind business cycles in the true model then my identification procedure will be able to generate unbiased estimates of the impact effects of the IST news shock and recover their dynamics, while producing downward biased estimates at longer horizons. Moreover, I also showed that under the assumption that IST news shocks are not the main force behind business cycles the identification procedure performs fairly well and produces a quite moderate downward bias at longer horizons that is much smaller than that generated by IST news-driven models. Hence, given the very strong empirical results obtained in Section 3, one can deduce that it is likely that these results were generated by a model in which IST news shocks are the main driver of business cycles. Furthermore, the downward bias of the estimated importance of IST news shocks suggests that the empirical results
of this paper can be viewed as a lower bound of the true role of IST news shocks in the business cycle.

The results of this paper provide an important indication that the focus of DSGE model builders should be on developing a suitable structure in which IST news shocks are the major force behind business cycles as well as the long-run variation in output and IST. As the recent results in Khan and Tsoukalas (2012) and Schmitt-Grohé and Uribe (2012) demonstrate, modern DSGE models are not equipped yet with the necessary ingredients with which IST news shocks can become the main driver of the business cycle. Hence, an important avenue of research in the future should be one in which the development of theoretical macro models that are consistent with IST news shocks being a main force behind business cycles. Moreover, the results of this paper indicate that IST news shocks imply a significant long run increase in IST which drives a significant permanent increase in the non-stationary real aggregates, i.e. output, investment, and consumption. This result 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 literatures 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. This literature has mainly focused on imposing restrictions on the sign of impulse responses (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)). My method is new with respect to the sign restrictions literature in two important respects. First, it does not impose restrictions of the effects of the shocks but rather on 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 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 (2012) obtained similar results on the business cycle implications of IST news shocks 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 (2012) 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 1990’s and early 2000’s 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 (2012).4

Moreover, this paper applies a stationary VAR specification which allows inference on the long-run implications of IST news shocks, as opposed to Ben Zeev and Khan (2012) who focused only on the business cycle implication of the latter shocks and thus used a non-stationary levels specification.5 The stationary VAR specification is necessary as it generates consistent estimates of the long-run impulse responses, as opposed to non-stationary VAR specifications (Phillips (1998)), which is important for the suitability of my identification approach as some of the restrictions pertain to long-run horizons. Having the ability to study the long-run implications of IST news shocks is important given the view that IST is an important driver of long-run economic growth

4While the results from the two identification procedures are similar, the median correlation between this paper’s identified shocks and the Ben Zeev and Khan (2012) 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 identification restrictions imposed in the two identification strategies.

5I also computed the median correlation between this paper’s shocks and the Ben Zeev and Khan (2012) shock series obtained from a stationary VAR specification and found it to be largely unchanged at 61%. This is an indication that the wedge between the two shocks is not driven by how the VAR is specified but rather by the type of identifying restrictions that are imposed in the two identification schemes.
(e.g. Greenwood et al. (1997)). As shown in Sections 3 and 4, the empirical evidence is consistent with the latter view as IST news shocks are found be the major force behind the long-run variation in output and IST.

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 then presents Monte Carlo evidence that is consistent with notion that IST news shocks are the main force behind business cycles. The final section concludes.

2 Identification Method

Prior to presenting the identification method in detail, I will first explain the underlying framework and the assumptions employed in this paper.

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

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

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 \( j = C, I \), and \( \Upsilon_t \) 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. 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. 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.

I assume 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 IST news shocks:

\[\begin{align*}
\epsilon_t &= \epsilon_{t-1} + g_{t-j} + \eta_t \\
g_t &= \kappa g_{t-1} + \epsilon_t
\end{align*}\]

Here technology, denoted by \(\epsilon_t\), follows a unit root process where the drift term itself 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. \(\eta\) is the conventional unanticipated IST shock.

6For 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 (e.g. Justiniano et al. (2011)). Moreover, Basu et al. (2010) find that the capital share for the services and non-durables sector is 0.36 whereas that of equipment and software investment and consumer durables is 0.31. Given that the two shares are relatively close, and that it is reasonable to assume that in the long run factor inputs can freely reallocate, it seems sensible to assume that the the long-run variation in RPI is driven by unanticipated IST shocks and IST news shocks.

7A similar process was used by Leeper and Walker (2011), Leeper et al. (2012), and Barsky and Sims (2011, 2012). 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 \(j\) periods into the future after which it will continue to gradually and persistently increase until reaching some new higher steady state. If \(\kappa\) were to equal zero there be would no gradual rise but rather a jump in technology \(j\) periods into the future after which technology will remain at that higher level permanently.
ipated technology shock. Given the timing assumption, \( e_t \) has no immediate impact on the level of IST but portends future changes in it. Hence, it can be defined as a technology news shock. The identification restrictions that I impose below so as to identify the news shock are consistent with Equations (2) and (3) which imply that the unanticipated shock and the news shock account for all of the variation in technology at all horizons where the news shock has no effect on current technology.

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

### 2.2 Generating the Set of Admissible Models

My 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 solutions or a set of solutions. As will be explained below, this set of solutions will constitutes 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 \( k \times 1 \) vector of observables of length \( T \) and let the VAR in the observables be given as

\[
y_t = B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p y_{t-p} + B_c + u_t
\]

where \( B_i \) are matrices of size \( k \times k \), \( p \) denotes the number of lags, \( B_c \) is a \( k \times 1 \) vector of constants, and \( u_t \sim i.i.d. \ N(0, \Sigma) \) is the \( k \times 1 \) vector of reduced-form innovations where \( \Sigma \) is the variance-covariance matrix of reduced-form innovations. Without loss of generalization, it is assumed that
technology constitutes the first variable in system. For future reference, let the \((kp + 1)xk\) \(B = [B_1, \ldots, B_p, B_c]\) 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 \(\Sigma\).

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

\[ u_t = Ae_t \]  

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 \(\Sigma\)), the entire space of permissible impact matrices can be written as \(CD\), where \(D\) is a \(k \times k\) orthonormal matrix \((D' = D^{-1} \text{ and } DD' = I, \text{ where } I \text{ is the identity matrix})\).\(^8\)

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 \(D\) so as 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), Mountford and Uhlig (2009), 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 \(\Sigma\), and identification matrices \(D\) under the assumption of a 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.\(^9\)

The procedure for randomly drawing models can be described as follows:

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\(^8\) In consistence with the SVAR literature, I assume here that the number of economic shocks is equal to the number of observables. The results are not changed if a larger number of shocks is assumed. Nevertheless, computational time is reduced significantly with a smaller number of shocks and thus this assumption is maintained.

\(^9\) Specifically, I assume a standard diffuse prior on the VAR reduced form parameters \(B\) and \(\Sigma\). Moreover, note 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.
1. Randomly draw a $k \times k$ 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 $\Sigma$ and denote it by $C$.

3. Use orthonormal matrix $D$, cholesky factor matrix $C$, and coefficient matrix $B$ to compute impulse responses and economic shocks via the orthogonalization $A = CD$.

4. Repeat steps 1-3 1,000,000 times.

Steps 1 and 2 are needed to draw the identification matrix $D$ and reduced form VAR parameters $B$ and $\Sigma$, 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 three 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 $(B, \Sigma, D)$ 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 1,000,000 such matrix triplets, or models, in accordance with Steps 1-3 from which only the admissible models will be 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 sum in the 1997-1999 period followed by a negative sum in the bust period of 2000:Q1-2003:Q1 which is at least 25% in absolute value of the boom period sum.\(^\text{10}\)

\(^{10}\)To be clear, the maximum 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 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.
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 $e_t$.\footnote{So as to ensure that the identified shock is not a measurement error or some other economic shock that also experienced large realization in the boom period (e.g, noise shocks), I also imposed on the identified shock to 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 models did the identified shock explain less than 5% of the long-run variation in RPI.}

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 boom period is the most apparent period in which positive IST news shocks realized, in accordance with both the common view that the boom period was an IST news- driven period. The bust restriction requires that at least a 25% correction of the overly optimistic expectations of the late 1990's 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. For the benchmark results I estimate a VAR with seven variables: RPI, output, hours, consumption, investment, inflation, and interest rates. Before proceeding, a brief discussion of the data is given. Then, the main empirical results are presented in detail.

3.1 Data

RPI is measured in the standard way as a consumption deflator divided by a quality adjusted investment 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 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:Q1-2012:Q1. I use this updated series as a measure for IST.12

The nominal series for output, consumption, and investment, data 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, 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 log of total hours worked in the non-farm business sector. Inflation is measured as the percentage change in the CPI for all urban consumers, and interest rate, the nominal interest rate is the three month Treasury Bill rate.13 My benchmark data series span the period 1959:Q1-2012:Q1.

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 hours, inflation, and interest rates, which are assumed to be stationary and enter the system in levels, all other variables enter the system in their first differences. 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 VAR with three lags. The results are robust to using a different number of lags. 1,000,000 models are generated via the procedure described by Steps 1-4. I then check whether the identifying assumption holds for each model and keep only the admissible models. The set of admissible models consists of 1635 models.

Figures 2 and 3 show the posterior distribution of impact impulse responses and contribution

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12I 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.

13To convert monthly population, inflation, and interest rate series to quarterly series, I use the last monthly observation from each quarter.
to forecast error variance (FEV) of the variables of the IST news shock at the two year horizon, respectively. Moreover, Figures 4 and 5 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 negative.

It is apparent from these four figures that favorable IST news shocks raise the real aggregates (output, hours, investment, and consumption) on impact and drive the bulk of their business cycle variation.\textsuperscript{14} The median impact effects 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 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. Moreover, the median contributions to the long run variation of output, consumption, and RPI are 52\%, 50\%, and 78\%, respectively, whereas that for investment is only 20\%.\textsuperscript{15} These long run contributions indicate that IST news shocks have more of a hump-shaped effect on investment compared to 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 the long-run variation in RPI.

3.3 Time Series of Identified Shocks

Figure 6 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

\textsuperscript{14}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 at 6\%, 8\%, 6\%, and 4\%, respectively. These results are available upon request from the author.

\textsuperscript{15}Note that these estimates are not shown in Figures 4 and 5 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.
the actual series.\textsuperscript{16} 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 1990’s 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 6 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 seven 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 is the concern that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The third issue pertains to the possibility that hours are not necessarily stationary and thus should perhaps enter the system in first differences rather than in levels. The fourth 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 fifth 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 sixth 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.\textsuperscript{17}

\textsuperscript{16}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.

\textsuperscript{17}I have also confirmed the robustness of the results to different lag specifications in the VAR. These results are available upon request from the author.
4.1 Addressing Potential Invertibility Issues

Leeper et al. (2012) and Sims (2012) have highlighted that the presence of news shocks about future fundamentals can pose difficulties for an econometrician drawing inference based on identified VAR’s. 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. From a practical standpoint, one approach to is to improve the econometrician’s information set so that it is better aligned with those of the private agents in the economy. Using Monte Carlo evidence, Sims (2012) shows that this approach can either ameliorate or eliminate the invertibility problem. While the benchmark VAR does include the main macroeconomic variables, both real and nominal, it still may be the case that more information needs to be added so as to attain better identification. Towards this end, I add a measure of stock prices (Beaudry and Portier (2006)) to the benchmark VAR as it is reasonable to assume that stock prices contain information about future IST progress.\footnote{The measure of stock prices used is 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. The results remain unchanged if the stock prices are not in per capita terms.}

Figures 7a-8b correspond to the Figures 2-5 with the only difference being that now the benchmark VAR is replaced by a larger VAR that includes stock prices. The figures are based on 1,000,000 randomly generated models from which a total of 181 admissible models were collected. Similar to the benchmark case (Figures 2-5), favorable IST news shocks raise the real aggregates on impact and drive the bulk of their business cycle variation. 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, confirming the view that the latter information variables contain valuable information about the future value of IST. Specifically, the median contribution of IST news shocks to output, hours, investment, and consumption are 56%, 52%, 51%, and 55%, respectively, while that to the variation in stock prices is 36%. Moreover, all of the latter variables jump on impact following the news shock. That the median impact effects of IST news on stock prices is so significant at 4.3% is an indication that stock prices contain important information about the future value of IST.
4.2 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 (e.g. Stock and Watson (2007)), are essentially the same as the large sample results.

Figures 9a-10b correspond to Figures 2-5 with the only difference being that the former figures were based on a post 1982 sub sample (1983Q1-2012Q1). The figures are based on 1,000,000 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 as IST news shocks drive the bulk of the business cycle variation in the real aggregates as well as the long run variation in RPI. Moreover, IST news shocks 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 contribution to the long run variation in RPI is 71% 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.

4.3 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. So as 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 first difference form.

Figures 11a-12b correspond to Figures 2-5 with the only difference being that the former are obtained from a VAR in which hours are assumed to be non-stationary and thus enter the system in first difference form. The figures are based on 1,000,000 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. Figures 10a-11b emphasize that 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 12a 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 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.

### 4.4 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.\(^{19}\) So as to try to assess the relation between my identified news shocks and credit spreads, I applied 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).

Figures 13a-14b correspond to Figures 2-5 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 1,000,000 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, raise consumption, and decrease investment.

\(^{19}\)Specifically, the estimated shock from Justiniano et al. (2011) represented a shock to the transformation of investment goods to capital goods, rather than the transformation of consumption goods into capital goods. While the latter usually represents IST shocks in DSGE models, the former can also be viewed as a shock to the technology with which capital goods are produced and thus as a shock to IST.
lower inflation, and to drive the majority of the business cycle variation 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 while 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 the spread. Given that the latter can be viewed as a shocks to the functioning of credit markets, this low correlation can seen as an indication that the results of this paper are not driven by credit supply disturbances.\footnote{One can also not rule out the possibility that the VAR innovation to the spread also contains information about future IST, similarly to how stock prices do, in addition to representing pure credit supply shocks. The evidence from this exercise provides some support for this view as the long-run effect of the spread innovation on RPI is -0.26%, i.e. a surprise rise in the spread implies that RPI will fall in the long-run, thereby providing a channel by which the VAR innovation and the IST news shocks could be negatively correlated. While this long-run effect is not big, it still indicates that some information on future IST is contained in the spread innovation thus further undermining the possibility that the results of this paper are driven by pure credit supply shocks.}

4.5 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 1990’s 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 1990’s news shocks portended future increase in measured TFP. Such a delayed relation between better quality of capital goods and measured TFP can be explained by the general-purpose technology (GPT) story (e.g. Bresnahan and Trachtenberg (1995) whereby ICT constitutes a GPT that leads to fundamental changes in the production process of the sectors using the new ICT-related goods thereby raising measured TFP in these sectors in the long-run. Basu and Fernald (2007) have provided U.S industry results that support this story. To examine whether such a possible link is
plausible, I applied my identification procedure on a VAR that includes a measure of TFP.  

Figures 15a-16b correspond to Figures 2-5 with the only difference being that the former are obtained from a VAR in which TFP is included. The figures are based on 1,000,000 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 negligible median effect on TFP at both short-run and medium-run horizons. At the long-run horizon, which is not shown in the figures, there is a moderate effect with the median long-run contribution amounting to only 13%. Thus, one may deduce from this that there seems to exist a transmission mechanism from the IST news shock to long-run TFP which is consistent with the GPT story, though this transmission mechanism is one of moderate importance.

4.6 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. Towards this end, Figures 17a-18b correspond to Figures 2-5 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 1,000,000 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 of the real aggregates (a median share of 63%, 66%, 60%, and 56% of the two year variation 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%.

21 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).

22 I also verified that the results are unchanged when the output deflator is used instead of the consumption deflator.
4.7 Cross-Correlation 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. So as to address this concern, I computed 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, Romer and Romer (2010) tax shock measure, shock to the real price of oil, the Ramey (2011) government 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 four variables on four lags.

The results are presented in Figure 19 where the median and 10th and 90th percentiles of the correlation between the IST news shocks and up to four lags and leads of each of the other five disturbances are shown. The results indicate that the cross-correlations are small, with the median correlation never exceeding 17% in absolute value. Thus, the main results of the paper are not driven by other structural disturbances.

5 Monte Carlo Evidence

In this section I will present Monte Carlo evidence that the results of this paper are fairly reliable in the sense that they are unlikely to have been generated by a model in which IST news shocks are not the main force behind business cycle. Three Monte Carlo experiments are considered. First, I will show results from an experiment in which the true model is an IST news driven model, i.e. IST news shocks generate business cycle comovement and drive over 50% of the business cycle variation in the real aggregates. Second, results from a simulation in which IST news shocks explain less than 50% of business cycles will be shown. Lastly, I will consider an experiment in which the boom-bust

\[\text{(17)}\]

Note that the only shock the IST news shock appears to be somewhat correlated with is the Barsky and Sims (2011) TFP news shock. As discussed in the previous section, the fairly moderate median correlation of 17% can be explained by the general-purpose technology (GPT) story (e.g. Bresnahan and Trachtenberg (1995) whereby ICT constitutes a GPT that leads to fundamental changes in the production process of the sectors using the new ICT-related goods thereby raising measured TFP in these sectors in the long-run.
restriction does not hold. The true data generating process for each experiment is obtained from applying Steps 1-3 from the algorithm in Section 2.2 and then imposing suitable restrictions which will be described below. Each model is then used to generate artificial data via randomly drawing the vector economic shocks, $e_t$, from the standard normal distribution.

5.1 Simulation from IST News-Driven Models

The models considered in this section are IST news-driven. These models comply with the following restrictions:

1. two shocks, belonging to the vector of economic shocks $e_t$, drive at least 90% of the long-run variation in RPI.

2. One of these two shocks, defined as the IST news shock, has its maximal three year moving sum in the 1997-1999 period followed by a negative sum in the bust period of 2000:Q1-2003:Q1 which is at least 25% in absolute value of the boom period sum.

3. This IST news shock raises the real aggregates and drives at least 50% of their two year variation.

Restriction 1 has been used in the empirical section as well and is aimed at obtaining models that comply with macroeconomic theory as given by Equation 1. Restriction 2 ensures the existence of an IST news shock, which is defined to be a shock that has a long-run effect on RPI and that exhibits a boom-bust like pattern in the late 1990’s early 2000’s period.\textsuperscript{24} Lastly, the last restriction guarantees that the model is IST news-driven in the sense that the latter shocks are the main force behind business cycles.

I collect a total of 100 models that conform to Restrictions 1-3. Each model is used to generate artificial data via randomly drawing the vector economic shocks from the standard normal distribution. I obtain the period in which the the maximal three year moving average takes place for the IST news shock series and then draw the subsequent 13 period shock sub-series from a

\textsuperscript{24}In accordance with the empirical analysis, I also make sure that this shock explains at least 5% of the long-run variation in RPI so as to avoid confounding it with potential measurement errors or other shocks that had big realizations in the boom-bust period (e.g. noise shocks).
standard normal distribution with a mean that is 53% in absolute value of the maximal three year moving average. This implies a mean correction of expectations 57%, in accordance with the empirical findings of the previous sections. Finally, I apply the identification procedure on each artificial data set by drawing 10,000 models and collecting only the admissible models as was done in Section 3. I assume that the timing of the maximal three year moving average is known to the econometrician. Thus, I impose the boom-bust restriction in accordance with the true timing of the boom-bust episode.\footnote{In Section 5.3 I consider the case in which the econometrician imposes the boom-bust restriction on the late 1990's early 2000's period erroneously.} I then collect the estimated impulse responses, FEV contributions, and identified shocks series.

Figures 20a and 20b show the average across simulations of the median and 10th and 90th percentile impulse responses and 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. It is apparent that the estimated impulse responses follow the dynamics of the true impulse responses very well. The timing of the peak effects are well identified and the median impact effects on the real aggregates are quite close to the true impact effects. Nevertheless, at longer horizons it is evident that the estimated responses are downward biased. Moreover, there is also downward bias in the estimates of the FEV contributions to the real aggregates’ variation. In particular, whereas the estimated mean 90th percentile business cycle contributions to real aggregates’ variation are quite close to the true ones, the estimated median contributions only amount to 41% for output and investment, 37% for consumption, and 46% for hours, compared to a mean true contribution of about 70% for these variables.\footnote{These results are consistent with findings of Canova and Paustian (2011) that using sign restrictions to identify very persistent shocks with large explanatory power for the endogenous variables results in downward biased estimates.} So as to obtain further information on the downward bias feature, I also computed the probability that the estimated median contribution to each real aggregate’s business cycle variation is higher than the corresponding true contribution and found that underestimation took place for output, hours, investment, and consumption in 100%, 96%, 92%, and 96% of the Monte Carlo replications, respectively. These results emphasize that the estimated median contribution can be viewed as a lower bound of true importance of IST news shocks.
The results on the other variables in the model, RPI, inflation, and interest rates, are generally similar to those on the real aggregates. With respect to RPI, it is apparent that the response is well identified until the five year horizon from which point a downward bias starts to persist in a gradual manner. At the long-run horizon, not shown in the Figures 20a and 20b, this bias is quite significant with the estimated median response amounting to only 55% of the true mean long-run effect. Lastly, also note that the responses of inflation and interest rates are recovered fairly well though the effect on inflation on impact and the response of interest rates at longer horizons are moderately underestimated.

I complement Figures 12a and 12b with results on the coverage rates for the real aggregates, i.e. the probability that the true response and contribution to the FEV fall within the estimated credible interval at the impact, one year, and two year horizons. These results are presented in Table 1. It is evident that in the majority of the Monte Carlo replications the 80% interval of contains the true response and contribution at the impact horizon. Nevertheless, consistent with the results in Figures 12a and 12b, the coverage rates decline as the horizon gets longer.

Overall, the results of this section are quite informative along two dimensions. First, they indicate that my proposed identification approach is capable of identifying both the impact effects of the shock on the real aggregates as well as the true dynamics. Second, the apparent downward bias at longer horizons indicates that the empirical results of this paper can be viewed as a lower bound with respect to the true importance of IST news shocks for business cycle fluctuations.

5.2 Simulation from Non IST News-Driven Models

I now generate artificial data from models in which IST news shocks are not the main force behind the business cycle. The shocks as well as the boom-bust IST news shocks sub-series are randomly drawn precisely in the same manner as the in the Monte Carlo experiment of the previous section. Now, I only consider as the true data generating process models in which the IST news shock

\footnote{Note that most of these coverage rates are lower than the nominal rate (80%). As Canova and Paustian (2011) points out, coverage rates for partially identities Bayesian VAR’s will in general be lower than the nominal rate and those obtained from classical VAR’s given the different approach to handling identification uncertainty that Bayesian VAR’s take, as discussed by Moon and Schorfheide (2012). Nevertheless, as will be seen in the next section, when IST news shocks are not the main force behind business cycles the coverage rates are higher and closely match the nominal rate.}
generates business cycle comovement but explains less than 50% of the business cycle variation in the real aggregates. Specifically, the following restrictions are imposed on the models used as the data generating processes in this section’s Monte Carlo experiment:

1. two shocks, belonging to the vector of economic shocks $e_t$, drive at least 90% of the long-run variation in RPI.

2. One of these two shocks, defined as the IST news shock, has its maximal three year moving sum in the 1997-1999 period followed by a negative sum in the bust period of 2000:Q1-2003:Q1 which is at least 25% in absolute value of the boom period sum.

3. The IST news shock raises the real aggregates and drives less than 50% of the business cycle variation (two year variation) in them.

The only different restriction with respect to the previous section is the last one. Note that this restriction implies that the IST news shock could still be important for the business cycle, though not the main driver of business cycle fluctuations. I collect 100 models that comply with the above three restrictions and randomly draw the all of the economic shock series in precisely the same manner as the in the Monte Carlo experiment of the previous section.

Figures 21a and 21b correspond to Figures 12a and 12b with the only difference being that now IST news shocks are not the main force behind business cycle fluctuations. It is apparent that the estimated median impulse responses and FEV contributions are quite close to their true counterparts at all horizons, though a moderate level of downward bias is still prevalent. Moreover, the estimated impulse responses follow the dynamics of the true impulse responses very well with the timing of the peak effects being well identified. As far as the identification of the responses of the nominal variables is concerned, it is clear that the effect on inflation is well identified whereas that of interest rates is underestimated.

So as to provide further information on the suitability of the identification procedure, Table 2 corresponds to Table 1 and reports results on the coverage rates for the real aggregates at the impact, one year, and two year horizons. It is evident that in the majority of the Monte Carlo replications the 80% interval of contains the true response and contribution at all of the tested
horizons. Overall, the coverage rates are quite close the nominal level of 80% for all variables and tested horizons.

The results from this Monte Carlo exercise demonstrate that under the assumption that IST news shocks in the true model are not the main force behind business cycle fluctuations, the identification procedure can recover the impulse responses and FEV contributions quite well. While there is still some downward bias prevalent in the estimated responses and FEV contributions, it is apparent that this bias is moderate and much smaller than that observed in the previous section. Given that the identification procedure is unlikely to result in upward biased estimates when IST news shocks are not the main drivers of business cycles and given that the empirical results from Section 3 point to a very strong role for IST news shocks as business cycle drivers, one can deduce that it is unlikely that a model in which IST news are not the main driver of business cycles is indeed the true model.

5.3  Could the Empirical Results be Spurious?

So as to examine whether the empirical results of this paper can potentially be spurious, I now generate artificial data from models in which the boom-bust restriction does not hold. Accordingly, I only consider as the true data generating process models in which neither of the two shocks that drive the long-run variation in RPI has its maximal three year moving sum in the 1997:Q1-1999:Q4 period. Moreover, all of the shocks are randomly drawn from the standard normal distribution without placing any restrictions on the drawn shocks in the period that follows a boom period. Specifically, the following restrictions are imposed on the models used as the data generating processes in this section’s Monte Carlo experiment:

1. two shocks, belonging to the vector of economic shocks $e_t$, drive at least 90% of the long-run variation in RPI.

2. neither of these two shocks has its maximal three year moving sum in the 1997-1999 period.

Note that the second restriction implies that there is not a shock that drives RPI in the long run and also conforms to the boom-bust restriction. I collect 100 models that comply with the above two restrictions and randomly draw all of the economic shock series from the standard normal
distribution. I then apply my empirical identification procedure on each artificial data set while erroneously imposing the late 1990’s early 2000’s boom-bust restriction.

As the aim of this Monte Carlo experiment is to examine whether my identification procedure could spuriously generate the empirical results from Section 3, I will now present the results that the identification procedure spuriously generated. Accordingly, Figures 22a and 22b show the average across simulations of the median and 10th and 90th percentile impulse responses and contributions to the variables’ variation of the identified business cycle shock over a ten year horizon, respectively.\textsuperscript{28} It is evident that the estimated median impulse responses and FEV contribution are very small. In particular, the estimated median contribution to the business cycle variation in output, investment, consumption, and hours are 15%, 18%, 9%, and 15%. This is an indication that the results of this paper are very unlikely to have been spuriously generated.

6 Conclusion

This paper has provided robust evidence that IST news shocks are the main force behind business cycle fluctuations, are deflationary, and raise nominal interest rates. I applied a novel identification approach that exploits the view that the late 1990’s early 2000’s boom-bust period can be characterized as an IST news-driven episode and identified an IST news shock as the shock that 1) has a long-run effect on RPI and 2) has its maximal three year moving average in the period of 1997-1999, where the maximum is computed with respect to all other three year moving averages within the shock series itself. After applying this identification procedure to real data, I conducted a set of Monte Carlo experiments that aimed at examining the reliability of the empirical results. The evidence from the Monte Carlo experiments clearly indicated that the empirical results of this paper are likely to have been generated by an IST news-driven model.

In accordance with the Monte Carlo evidence of Canova and Paustian (2011) that using sign restrictions to identify persistent shocks with large explanatory power for the endogenous variables results in downward biased impulse response estimates, I found that when IST news shocks account for the bulk of the variation in the real aggregates the resulting estimates are downward biased.\textsuperscript{28}

\textsuperscript{28}Only in 57 out of the 100 replications the resulting estimated set of model was not null. The results are based on these 57 replication.
In contrast, when IST news shocks are not the main force behind business cycle the resulting downward bias is moderate and much smaller than the one generated by IST news-driven models. Overall, these findings indicate that the strong empirical results found in this paper can be thought of as representing a lower bound of the true role that IST news shocks play in the business cycle.

An important implication from this paper is that an identification strategy that relies on information regarding a particular time period in which it is widely agreed that large positive/negative realizations of a specific shock took place can provide a useful and informative identification method. Such an identification strategy constitutes a novel approach to identifying shocks in that it doesn’t follow the standard practice of imposing restrictions on the effects of the shocks, but rather the shocks realizations themselves. An important appealing feature of this approach is that it doesn’t require imposing any restrictions on the absolute size of shock realizations, on which we usually do not have any information, but rather on the relative size of certain shock realizations, on which we can obtain information from the timing of large macroeconomic events. Hence, any shock on which we have reliable information pertaining to certain periods in which it experienced relatively large realizations could potentially be identified by this identification approach.

Appendix A Posterior Distribution of Reduced Form VAR Parameters

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

$$Y = XB + U$$

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 $\Sigma$ 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:

$$\text{vec}(B) | \Sigma \sim N(\text{vec}(\bar{B}_0), \Sigma \otimes N_0^{-1})$$

$$\Sigma \sim IW_k(v_0S_0, v_0)$$
where $N_0$ is a $kpxkp$ positive definite matrix, $S_0$ is a $kxk$ covariance matrix, and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(B) \mid \Sigma \sim N(vec(B_T), \Sigma \otimes N_T^{-1})$$

$$\Sigma \sim IW_k(v_T S_T, v_T)$$

where $v_T = T + v_0$, $N_T = N_0 + X'X$, $B_T = N_T^{-1}(N_0 \hat{B}_0 + X' \hat{X} \hat{B})$, $S_T = \frac{v_T}{v_T} S_0 + \frac{T}{v_T} \hat{\Sigma} + \frac{1}{v_T} (\hat{B} - \hat{B}_0)' N_0 N_T^{-1} X' X (\hat{B} - \hat{B}_0)$, $\hat{B} = (X'X)^{-1} X' Y$, 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 $\hat{B}_0$. This implies that the prior distribution is proportional to $|\Sigma|^{-(k+1)/2}$ and that $v_T = T$, $S_T = \hat{\Sigma}$, $B_T = \hat{B}$, and $N_T = X'X$. Thus, the posterior simulator for $B$ and $\Sigma$ can be described as follows:

1. Draw $\Sigma$ 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 $\Sigma$'s.
References


Table 1: **IST News-Driven Models - Monte Carlo Coverage Rates for Impulse Responses and FEV Contributions.**

<table>
<thead>
<tr>
<th></th>
<th>Impulse Response, FEV Contribution</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Impact Horizon</td>
</tr>
<tr>
<td>Output</td>
<td>0.69,0.51</td>
</tr>
<tr>
<td>Investment</td>
<td>0.67,0.56</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.41,0.39</td>
</tr>
<tr>
<td>Hours</td>
<td>0.77,0.68</td>
</tr>
</tbody>
</table>

**Notes:** This table presents the coverage rates for the real aggregates from the Monte Carlo experiment of section 5.1, i.e. the probability that the true response and contribution to the FEV fall within the estimated credible interval at the impact, one year, and two-year horizons. The true models contain IST news shocks that are the main driver of business cycles. The coverage rate for the impulse responses are shown in the left sub-columns whereas that for the FEV contributions is given by the right ones.

Table 2: **Non IST News-Driven Models - Monte Carlo Coverage Rates for Impulse Responses and FEV Contributions.**

<table>
<thead>
<tr>
<th></th>
<th>Impulse Response, FEV Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Impact Horizon</td>
</tr>
<tr>
<td>Output</td>
<td>0.82,0.80</td>
</tr>
<tr>
<td>Investment</td>
<td>0.91,0.82</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.62,0.76</td>
</tr>
<tr>
<td>Hours</td>
<td>0.82,0.69</td>
</tr>
</tbody>
</table>

**Notes:** This table presents the coverage rates for the real aggregates from the Monte Carlo experiment of section 5.2, i.e. the probability that the true response and contribution to the FEV fall within the estimated credible interval at the impact, one year, and two-year horizons. The true models contain IST news shocks that are not the main driver of business cycles. The coverage rate for the impulse responses are shown in the left sub-columns whereas that for the FEV contributions is given by the right ones.
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: Normalized Histogram of Impact Impulse Responses to an IST News Shock (Benchmark Case).

Notes: This figure presents the posterior distribution of the impact impulse responses to an IST news shock. In this figure, 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 the long run effect of the shock on RPI was negative.
Figure 3: Normalized Histogram of the Contribution of IST News Shocks to the Forecast Error Variance of the Variables at the Two Year Horizon (Benchmark Case).

Notes: 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.
Figure 4: The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks (Benchmark Case).

Notes: 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.
Figure 5: The Median and 90th and 10th percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables (Benchmark Case).

*Notes:* The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions.
Figure 6: Identified IST news shock time series (smoothed) and U.S. recessions.

Notes: The U.S. recessions are represented by the shaded areas. So as 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 $\varepsilon_t$ is the median of the 1635 identified shock series. The plotted series begins in 1960:Q4 and ends in 2012:Q1.
Figure 7: VAR With Stock Prices: (a) Impact Response Histogram; (b) Two Year FEV Histogram

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from a VAR that includes stock prices). 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 a VAR that includes stock prices).
Figure 8: VAR With Stock Prices: (a) Impulse Responses; (b) Contribution to FEV

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).
(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 a post 1982 Sample). 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 a post 1982 Sample).
Figure 10: Post 1982 Sample: (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 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 11: Non-Stationary Hours: (a) Impact Response Histogram; (b) Two Year FEV Histogram

(a) Normalized Histogram of Impact Impulse Responses (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 entering hours in VAR in first difference form). 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 entering hours in VAR in first difference form).
Figure 12: 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 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 first difference form).
Figure 13: VAR With Credit Spread: (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 a VAR that includes a credit spread variable). 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 a VAR that includes a credit spread variable).
Figure 14: 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).
Figure 15: VAR With TFP: (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 a VAR that includes TFP). 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 a VAR that includes TFP).
Figure 16: VAR With TFP: (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 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 17: Alternative RPI Measure: (a) Impact Response Histogram; (b) Two Year FEV Histogram

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from a VAR in which RPI is measured using NIPA investment deflators). 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 a VAR in which RPI is measured using NIPA investment deflators).
Figure 18: 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 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 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 19: 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.
Notes: The figures are based on an experiment in which the true model contains IST news shocks that are the main force behind business cycle fluctuations. Panel (a): The solid line is the average estimated median impulse response across Monte Carlo replications, the dashed lines are the 90th and 10th 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 replications, the dashed lines are the 90th and 10th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.
Figure 21: Monte Carlo Evidence - Non IST News-Driven Models: (a) Impulse Responses ; (b) Contribution to FEV

Notes: The figures are based on an experiment in which the true model contains IST news shocks that are not the main force behind business cycle fluctuations. Panel (a): The solid line is the average estimated median impulse response across Monte Carlo replications, the dashed lines are the 90th and 10th 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 replications, the dashed lines are the 90th and 10th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.
Figure 22: Monte Carlo Evidence - Spurious Case: (a) Impulse Responses ; (b) Contribution to FEV

Notes: The figures are based on an experiment in which the boom-bust restriction does not hold, i.e. sum of IST news realizations in late 1990’s is not maximal. Panel (a): The solid line is the average estimated median impulse response across Monte Carlo replications, the dashed lines are the 90th and 10th 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 replications, the dashed lines are the 90th and 10th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.