A New VAR-Based Approach to Identifying News Shocks

Nadav Ben Zeev *
European University Institute

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Abstract

The basic identifying assumption underlying news driven models is that technology is driven by two shocks, one being the unanticipated technology shock and the other being the news shock, where the news shock doesn't have an impact effect on technology but rather portends future changes in it. This paper proposes and implements a novel VAR-based approach that generates the set of models consistent with the latter identifying assumption. The method is applied to investment-specific technology (IST) where it is shown that favorable IST news shocks raise output, hours, investment, and consumption, and account for the majority of their business cycle variation. Moreover, these shocks explain the bulk of the long-run variation in IST.

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Contact details: Max Weber Programme, European University Institute, Villa la Fonte, Via delle Fontanelle 20, 50014
E-mail: nadav.benzeev@eui.eu

1 Introduction

The notion that changes in expectations about future technology can be a driving force behind business cycles constitutes an appealing idea which has received growing attention in recent years following the pioneering work by Beaudry and Portier (2004). Identifying the role of these shocks in the macroeconomy is thus especially important as it can improve our understanding of the underlying source of economic fluctuations. Towards this end, I propose and implement a new VAR-based approach to identifying news shocks that generates the set of theory-consistent news driven models. This set contains models which comply with the basic assumption underlying news driven models that technology is driven by two shocks, one being the unanticipated technology shock and the other being the news shock, where the news shock doesn't have an impact effect on technology but rather portends future changes in it. In practice, my method generates the set of theory-consistent models by gathering all models in which at least 98% of the variation in technology at all horizons up to the 10 year horizon as well as the long-run horizon is driven by two shocks.[1,2] The proposed method is applied to investment-specific technology (IST) and is found to be very informative about the true data generating process. In particular, I show that favorable IST news shocks generate business cycle comovement, i.e. raise output, hours, investment, and consumption, and account for the majority of the business cycle variation in the latter variables as well as the long-run variation in IST.

The method I use in this paper is based on the sign restrictions Structural VAR (SVAR) literature which identifies shocks of interest by employing set identification whereby theory-consistent restrictions are imposed so as to generate the 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

[1]Ideally, one would require that 100% of the variation is explained by the two shocks. Nevertheless, given the potential presence of measurement errors the minimum threshold value of 98% seems a reasonable compromise.

[2]The long-run horizon is included so that the theory-consistent models would essentially comply with the theory at all horizons. The long-run contribution of the shocks is simply computed from their long-run permanent effect on technology. Alternatively, I could also require a 98% contribution of two shocks at all horizons up to a sufficiently long horizon, say 50 years, rather the medium term one of ten coupled with the long-run horizon. Nevertheless, while this alternative produces the same results it is much less efficient than the benchmark method in terms of computational time.

(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 that it incorporates both exclusion restrictions on the impact response of technology as well as restrictions on the forecast error variance decomposition of the technology variable. Moreover, to my knowledge, my paper constitutes the first attempt to identify news shocks via a variant of the sign restrictions approach which carries with it three main advantages. First, as Canova and Paustian (2011) demonstrate, the median of the distribution of responses is a good estimate of the true response and the approach has good size and excellent power properties even in small samples. Second, the proposed method seems to be particularly suitable for the identification of technology news shocks given that the latter imply a set of identifying restrictions that are common across news driven models and can be imposed in a straightforward manner. Specifically, news driven models generate identifying restrictions that imply a one to one correspondence between theory and identification, which renders the proposed method highly suitable for the identification of news shocks as its aim is to generate a set of theory-consistent models which comply with a variety of news driven models. Lastly, in contrast to previous papers which identified news shocks via point identification methods (e.g. Beaudry and Portier (2006), Beaudry and Lucke (2010), Barsky and Sims (2011), Forni et al. (2011), and Ben Zeev and Khan (2012)), my proposed method generates the entire set of potentially true models for a given reduced form VAR, rather than just one model, and thus is able to account for identification uncertainty.[3,4]

The results of this paper affirm the findings obtained by Ben Zeev and Khan (2012), who demonstrate that applying the Barsky and Sims (2011) method as well as various extensions of their method on IST rather than total factor productivity (TFP) generates results that are consistent with the ones obtained in this paper, i.e. that IST news shocks generate business cycle comovement and are the major force behind U.S. business cycles.[5] The proposed method of this paper is more

[3]Forni et al. (2011) differ from the other papers in that they estimated a Factor Augmented VAR which has the advantage of potentially ameliorating the non-invertibility problem whereby VAR innovations don't perfectly correspond to economic shocks. I address the non-invertibility issue in section 4.1.

[4]I follow the conventional approach to inference taken by the sign restrictions literature and perform Bayesian VAR estimation by computing the posterior distribution of models given an uninformative prior on the reduced form VAR parameters (see section 2.2 and Appendix A for details). Hence, the estimated set of theory-consistent models reflects not only identification uncertainty but also parameter uncertainty.

[5]Barsky and Sims (2011) identified the TFP news shock as the shock that is orthogonal to current TFP

robust and informative than the point identification method used by Ben Zeev and Khan (2012) as it accounts for identification uncertainty in addition to parameter uncertainty in contrast to point identification methods which only account for the latter. In particular, this paper's results are derived from not just one theory-consistent identification strategy but rather many theory-consistent identification schemes. The ability to account for identification uncertainty can be very important as there may be many potentially true models obtained from different theory-consistent identification schemes.[6] 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. 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 (e.g. Greenwood et al. (1997)). As shown in sections 3 and 4, this paper presents empirical evidence consistent with the latter view as IST news shocks are found be the major force behind the long-run variation in output and IST.

I conduct a battery of checks to establish the robustness of my benchmark results. Two important checks will now be highlighted. First, as emphasized by Leeper et al. (2012) and Sims (2012), the presence of news shocks may generate a non-invertibility problem whereby there's a wedge between VAR innovations and economic shocks. The reason for this is that news shocks also constitute unobserved state variables that are missing from the econometrician's information set thereby causing a discrepancy between the latter and the economic agents' information set. As

and which maximally explains future variations in TFP over a ten year horizon and found that TFP news shocks are an unimportant source of business cycles. Moreover, Forni et al. (2011) found similar results using a similar identification approach based on a Factor Augmented VAR. I also applied my method on TFP and found that TFP news shocks are a negligible source of the business cycle, in consistence with the result found in Barsky and Sims (2011) and Forni et al. (2011), though the requirement that 98% of the variation in TFP is driven by two shocks needed to be moderated to 96% as the former generated a null set of theory-consistent models. These results are available upon request from the author.

[6] I also generated all of this paper's results holding constant the reduced form VAR at the OLS estimates and was thus able to isolate identification uncertainty from parameter uncertainty. While the set of theory-consistent models obtained from the latter procedure was quite large (5383 models for the benchmark case), identification uncertainty turned out to be very small with the minimal impulse responses very similar to the maximal ones. These results are available upon request from the author.

Sims (2012) demonstrates via Monte carlo simulations, increasing the econometrician's information set can either alleviate or eliminate the invertibility problem. Towards this end, I add stock prices and consumer confidence to the benchmark and show that applying my identification procedure on the extended VAR generates the same results.[7] Second, recent research by Basu et al. (2010) has argued that the assumption that the relative price of investment, which I use as a measure of IST, fully reflects IST is too strong. The latter use input output tables to construct a aggregate measure of IST from industry specific technology innovations that is robust to a potential wedge between relative prices and IST. Regressing the real aggregates on their robust IST measure, Basu et al. (2010) found that IST unanticipated shocks reduce the real aggregates. So as to address the concern of the latter wedge, I allow all shocks to affect the relative investment price in the short and medium run while restricting that two shocks explain its long-run variation, i.e. unanticipated and IST news shocks.[8] Nevertheless, so as to distinguish between the two shocks, an additional restriction is needed. Towards this end, I show two sets of results from utilizing two different restrictions that are sufficient for pinning down the IST news shock. First, I use information from Basu et al. (2010) and impose on one of the shocks to have a negative effect on the real aggregates while identifying the remaining shock as the IST news shock. Second, I exploit the widely held view by economists that the late 1990's boom and subsequent early 2000's bust were strongly related to overly optimistic IST news shocks and their subsequent downward revision and impose on one of the shocks to behave in this boom-bust fashion. Overall, the results from these two identification schemes indicate that the benchmark results are left unchanged and are robust to a potential wedge between relative prices 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. The final section concludes.

[7] Beaudry and Portier (2006) showed that stock prices contain valuable information about future economic activity where as Barsky and Sims (2012) showed the same with respect to consumer confidence.

[8] This restriction is based on the assumption that IST is the sole long-run source of the relative price of investment (e.g. Fisher (2006) and Canova et al. (2010). Section 4.4.3 shows that the main results of the paper are robust to relaxing this restrictions as well which implies allowing all shocks to freely affect RPI at *all* horizons.

2 Identification Method

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

2.1 Identifying Assumptions

It is assumed that technology is well-characterized as following a stochastic process driven by two shocks. The first is the traditional unanticipated technology 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 technology news shocks:[9]

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

$$g_t = \kappa g_{t-1} + e_t \tag{2}$$

Here technology, denoted by ϵ_t, follows a unit root process where the drift term itself g_{t-1} follows an AR(1) process. Parameter κ describes the persistence of the drift term. η is the conventional unanticipated 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 (1) and (2) which imply that η_t and e_t account for all of the variation in technology at all horizons where e_t has no effect on current technology. I will now turn to explaining the identification strategy employed in the paper to identify news shocks.

2.2 Identification of News Shocks

My proposed method is based on the sign restrictions approach whereby a set of theory-consistent models is generated using the reduced form estimated VAR. I employ bayesian estimation and inference and therefor the set of theory-consistent models will also account for parameter uncertainty,

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

as will be explained below. I combine both exclusion restrictions on the contemporaneous response of technology as well as restrictions on the forecast error variation in technology at all horizons so as to identify the technology news shock. The latter is identified as the shock that has no impact effect on technology and which explains the remaining variation in technology not accounted for by the unanticipated shock.

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

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + B_c + u_t \tag{3}$$

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. Without loss of generalization, it is assumed that technology constitutes the first variable in system. For future reference, let the $(kp+1)$xk $B = [B_1, ..., B_p, B_c]'$ matrix represent the reduced form VAR coefficient matrix. Hence, the reduced form VAR parameters can be summarized by the coefficient matrix B and variance covariance matrix Σ.

It is assumed that there exists a linear mapping between the reduced-form innovations and structural shocks, ε_t, given as

$$u_t = A\varepsilon_t \tag{4}$$

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 ($D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).[10]

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 sign restrictions methods would generate set identification by obtaining the set of theory-consistent models. In the set identification approach

[10] 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.

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 theory-consistent models can be obtained by checking which models comply with the identifying 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 Σ, 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 explained in Appendix A, 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.[11] The procedure for randomly drawing models can be described as follows:

1. Randomly draw a $(k-1)$x$(k-1)$ matrix P of NID(0,1) random variables. Derive the QR decomposition of P such that $P = QR$ and $QQ' = I$.

2. Construct a new orthonormal kxk matrix D whose first column and row consist of a one and zeros thereafter while the other elements are the elements in matrix Q.

3. 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.

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

5. Repeat steps (1)-(4) 1,000,000 times.[12]

Steps 1-3 are needed to draw the identification matrix D and reduced form VAR parameters B and Σ. As discussed by Rubio-Ramirez et al. (2010), step 1 constitutes an efficient method for

[11]Specifically, I assume a standard diffuse prior on the VAR reduced form parameters B and Σ (see Appendix A for details).

[12]1,000,000 models are drawn in all of the identification schemes carried out in this paper apart from the case of the larger VAR in section 4.1 where I draw 16,000,000 models to generate a sufficiently large set of theory-consistent models.

generating orthonormal matrices. Step 2 ensures that technology is affected on impact only by the unanticipated technology shocks which corresponds here to the first column of D.[13] Appendix A describes the details of how the posterior simulator for the reduced form VAR parameters is implemented. Step 4 involves using the drawn matrices from the previous three steps and the orthogonalization $A = CD$ for the computation of the impulse responses. I generate 1,000,000 models in accordance with steps 1-4 from which only the theory-consistent models will be chosen to constitute the desired set of admissible models. In practice, it is checked if the resulting models comply with the assumption that technology is driven by two shocks by searching for models in which the unanticipated shock and an additional shock explain at least 98% of the variation in IST at all horizons up to the 10 year horizon as well as the long-run horizon. Models that don't comply with the latter condition are discarded while models that do are kept.

3 Empirical Evidence

In this section the main results of the paper are presented. For the benchmark results I estimate a VAR with five variables: a measure of IST, output, hours, consumption and investment. The findings indicate that all IST news driven models contain IST news shocks generate business cycle comovement and are the major force behind business cycles and the long-run variation in IST. Before proceeding, a brief discussion of the data is given. Then, section 3.2 presents the main empirical results in detail followed by a sensitivity analysis section which will provide evidence that the above results are robust.

3.1 Data

Proper identification of IST news shocks requires an appropriate measure of IST. I follow the standard approach taken by the IST literature (e.g. Greenwood et al. (1997, 2000), Fisher (2006), Canova et al. (2010), Beaudry and Lucke (2010), and Liu et al. (2011)) and use a quality adjusted

[13]The first row of D is simply one followed by zeros because in models where a variable (technology) that corresponds to the first row in the impact matrix A is affected on impact by only one shock (unanticipated technology shock) the corresponding row of D must have a one in its first component and zeros elsewhere. Moreover, so as to maintain orthogonality the corresponding column of D, which represents the unanticipated shock, must also have a one followed by zeros.

real investment price measure to gauge IST (Henceforth: RPI). This price is measured as a consumption deflator divided by a quality adjusted investment deflator. 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.[14]

While RPI is a standard proxy for IST in the literature, one may be concerned that the assumptions that warrant equality between RPI and IST do not hold. In particular, factors such as time varying sector specific markups, non-identical sectoral production functions, and limited sectoral reallocation can create a wedge between RPI and IST ((e.g. Basu et al. (2010) and Justiniano et al. (2011)), thus potentially limiting the ability to identify IST news shocks. In section 4.4, I will relax the identifying assumption that RPI is equal to IST and driven by two shocks and show that the results of this paper are robust to a potential wedge between RPI and IST.

The output measure used is the log of real GDP at a quarterly frequency. The consumption series is the log of real non-durables and services. The hours series is log of total hours worked in the non-farm business sector. These series are converted to per capita terms by dividing by the civilian non-institutionalized population aged sixteen and over. The output, investment, and consumption data are taken from the BEA; hours and population data are taken from the BLS. The population series in raw form is at a monthly frequency. It is converted to a quarterly frequency using the last monthly observation of each quarter. My benchmark data series span the period 1959:Q1-2012:Q1.

3.2 Benchmark Results

I apply my method on a VAR that includes five variables: RPI, output, investment and durables, non-durables and services consumption, and the log of total hours worked. Apart from hours, which

[14]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.

are assumed to be stationary and enter the system in levels, all other variables enter the system in their first differences. I tested for cointegration between the non-stationary variables using the maximum eigenvalue and trace statistic tests and found that a zero rank cannot be rejected at a 5% p value, i.e. there are no cointegrating vectors among the non-stationary variables. The system is estimated as a stationary VAR as opposed to a VAR in levels due to the superiority of the former over the latter in terms of the identification of the long-run impulse responses (Phillips (1998)). The Akaike information criterion favors three lags whereas the Schwartz and Hannan-Quinn information criteria favor two and one lags, respectively. As a benchmark, I choose to estimate a VAR with three lags. The results are robust to using a different number of lags.

I apply the procedure described by steps (1)-(5) and generate 1,000,000 models. I then check whether the identifying assumption holds for each model and keep only the theory-consistent models. The set of IST news driven models consists of 2650 models. Figures 1 and 2 show the posterior distribution of impact impulse responses and contribution to forecast error variance of the variables of the IST news shock at the two year horizon, respectively. Moreover, figures 3 and 4 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 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 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. The 10th percentile impact effects of IST news shocks on output, hours, investment, and consumption are 0.38%, 0.24%, 1.24%, and 0.28%, respectively, while the median impact effects are 0.50%, 0.35%, 1.66%, and 0.34%, respectively. All of the latter effects are economically significant and point to the strong business cycle comovement that the IST news shock generates. The 10th percentile contributions of IST news shocks to output, hours, investment and consumption at the two year horizon are 67%, 74%, 62%, and 54%, respectively, while the median contributions are 80%, 86%, 76%, and 71%, respectively, all indicating that IST news shocks are the major force behind the business cycle. Moreover, the median contributions to the long-run variation of output, consumption, and RPI are 60%, 64%, and 80%, respectively, whereas that for investment is only 16%.[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.

4 Robustness Checks

This section addresses four potentially important concerns regarding the analysis undertaken in the previous section. The first is that there may not exist a perfect linear mapping between VAR innovations and economic shocks. The second is that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The third is that hours are not necessarily stationary and thus should perhaps enter the system in first differences rather than in levels. The fourth is the assumption of equality between RPI and IST, which has been argued to be too strong of an assumption in recent work by Basu et al. (2010) and Justiniano et al. (2011).

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, in which case the true model is said to be non-invertible. From a practical standpoint, one approach to addressing potential non-invertibility 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. Towards this end, I add measures of stock prices (Beaudry and Portier (2006)) and consumer confidence (Barsky and Sims (2012)) to the benchmark VAR as

[15]Note that these estimates are not shown in figures 3-4 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.

it is reasonable to assume that these measures contain information about future IST progress.[16]

Figures 5a-6b correspond to the figures 1-4 with the only difference being that now the benchmark VAR is replaced by a larger VAR that includes stock prices and consumer confidence. It is assumed that consumer confidence is stationary and thus it is entered into the VAR in levels form like hours. The figures are based on 16,000,000 randomly generated models from which a total of 409 theory-consistent models were collected. Similar to the benchmark case (Figures 1-4), favorable IST news shocks raise the real aggregates on impact and drive the bulk of their business cycle variation. Interestingly, IST news shocks are also important drivers of the variation in stock prices and consumer confidence, 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 69%, 75%, 70%, and 60%, respectively, while those to the variation in stock prices and consumer confidence are 55% and 48%, respectively. Moreover, all of the latter variables jump on impact following the news shock. That the median impact effect of IST news on stock prices and consumer confidence is so significant at 5.5% is an indication that these information variables 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 VECM 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 7a-8b correspond to figures 1-4 with the only difference being that the former figures were based on a post 1982 sub sample (1983Q1-2011Q1). The figures are based on 1,000,000

[16]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. The consumer confidence data are from the Michigan Survey of Consumers, and summarize responses to a forward-looking question concerning aggregate expectations over a five year horizon. This series is available from 1960:Q1 and hence the sample period for the VAR is 1960:Q1-2012:Q1.

randomly generated models from which a total of 445 theory-consistent 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 as they raise the real aggregates on impact. The 10th percentile contributions of IST news shocks to output, hours, investment, and consumption at the two year horizon are 68%, 66%, 67%, and 62%, respectively, whereas the median contributions are 82%, 86%, 81%, and 80%, respectively. These estimates are an indication of the dominance of IST news shocks as business cycle drivers. Moreover, the median contribution to the long-run variation in RPI is 84% 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 ad thus enter the system in first difference form. Specifically, a VAR in which all variables enter in first difference form was estimated.

Figures 9a-10b correspond to figures 1-4 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 558 theory-consistent 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 9a-10b emphasize that the majority of the models contain IST news shocks that generate business cycle comovement and are the major driving force behind the business cycle variation in the real aggregates. Nevertheless, it is apparent that the response of hours is weaker relative to the benchmark response obtained from the benchmark model. In particular, while the hours response on impact is positive for over 85% of the models, it is still not as strong as the benchmark response obtained from the benchmark model. Moreover, the contribution of IST news shocks to hours business cycle variation is not as strong as the benchmark one though it is still significant with a median contribution of 52% at the two year horizon. Furthermore, over 70% of the models contain IST news shocks that explain more that 40% of the two year variation in hours. The results with respect to the other variables are quite similar quantitatively to the benchmark ones.

As figure 10a 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 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 Accounting for a Potential Wedge between RPI and IST

One may be concerned that the assumption of equality between RPI and IST may not hold, in which case it may not be appropriate to assume that RPI is driven solely by unanticipated and anticipated IST shocks. The assumptions needed for RPI to fully reflect IST are identical production functions, perfectly competitive sectors, and free sectoral re-allocation. Recent research (e.g. Basu et al. (2010) and Justiniano et al. (2011)) has argued that the assumption of equality between RPI and IST is too strong. The ptential wedge between RPI and IST can be illustrated by considering a two sector model structure along the lines outlined in Justiniano et al. (2011) with separate imperfectly competitive investment and consumption sectors. Both sectors are influenced by a common TFP shock and, in addition, the investment sector is affected by an IST shock. In this set up one can derive the following equilibrium equation linking IST progress with the relative price of investment

$$IST_t = \underbrace{\left(\frac{a_c}{a_I}\right)\left(\frac{mc_{C,t}}{mc_{I,t}}\right)\left(\frac{K_{C,t}}{L_C,t}\right)^{-(1-a_C)}\left(\frac{K_{I,t}}{L_{I,t}}\right)^{(1-a_I)}}_{\text{Wedge}}\left(\frac{P_{I,t}}{P_{C,t}}\right)^{-1} \tag{5}$$

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 Υ_t corresponds to investment-specific technology. From (5) it is clear that when the assumptions for the relative price of investment to fully reflect IST are not met, namely, identical production functions, perfectly competitive sectors, and free factor re-allocation, all of which are needed to ensure identical capital-labour ratios in the two sectors whereas the second one is needed for mark-ups to be zero and hence equal across sectors, a wedge arises between $(P_{I,t}/P_{C,t})^{-1}$ and IST_t. If such a wedge does exist, the identifying assumption of orthogonality with respect to RPI might not be appropriate given that the IST news shock may affect the relative price of investment through an impact effect on relative markups or relative capital-labor ratios due to possible limited sectoral reallocation of production factors.

Therefore, I will now relax both the exclusion restriction with respect to the impact response of RPI as well as the assumption that RPI is driven by two shocks at all horizons and allow all shocks to freely affect RPI both in the short run as well as the medium run, in accordance with equation (5). Specifically, a theory-consistent model now is a model which complies with the condition that in the long run only two shocks account for at least 98% of the variation in RPI. The rationale behind this restriction is that according to equation (5) the sole source of the unit root in RPI is IST, thus implying that in the long run nearly all of the variation in RPI is driven by unanticipated and anticipated IST shocks.[17] The assumption that IST is the sole source of the unit root in RPI is also the underlying identifying assumption made by papers that used long-run restrictions to identify unanticipated IST shocks (e.g. Fisher (2006) and Canova et al. (2010)). In consistence with equation (5), this assumption implies that all other shocks, as well as IST shocks, are free to affect RPI in the short run and the medium run. Nevertheless, in section 4.4.3 this assumption will also be relaxed and it will be shown that the main results of the paper are also robust to allowing all shocks to affect RPI at *all* horizons, including the long-run horizon.

Nevertheless, the latter restriction on the long-run response of RPI is not sufficient for the

[17]Note that IST will be the sole source of the unit root in RPI only if the capital shares across sectors were equal as free capital reallocation can be assumed to exist in the long run. 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, it seems reasonably to impose the restriction that nearly all of the long-run variation in RPI is driven by unanticipated IST shocks and IST news shocks. In section 4.4.3, I also show that the results are robust to relaxing this restriction thus allowing all shocks to affect RPI also in the long run.

identification of IST news shocks as more information is needed so as to distinguish between unanticipated IST shocks and IST news shocks. Hence, I will present two sets of results based on utilizing two different restrictions which can help distinguish between the two IST shocks and pin down the IST news shock. First, I utilize information from Basu et al. (2010) who used input-output tables and industry specific technology innovations to identify unanticipated IST shocks which are robust to a possible wedge between RPI and IST and found that unanticipated IST shocks generate a decline in output, hours, investment, and consumption on impact. Second, I exploit the widely agreed view that the late 1990's boom and subsequent bust were mostly related to overly optimistic expectations regarding information technology that were followed by a downward revision of these expectations.[18] After presenting the latter two sets of results, I will also present results that are obtained from relaxing the long-run restriction that IST is sole source of the unit root in RPI and merely rely on the restriction that the identified shock series behaves in accordance with the late 1990's-early 2000's boom-bust period.

Prior to presenting the results from utilizing the latter two sets of external information, I will first present the steps that need to be taken to randomly generate a large set of models from which the set of theory-consistent models will be formed. Given that all shocks are free to affect RPI on impact, the following modification to steps (1)-(5) from section 2.2 is to take place:

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

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

There are two important changes in the above algorithm with respect to the benchmark algorithm. The first is that step 2 from the benchmark algorithm is no longer needed given that all shocks

[18]Information technology 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.

are now free to affect RPI on impact. Hence, step 1 involves directly drawing a kxk orthonormal matrix D with no restrictions on it. The second modification pertains to step 3 which also instructs to collect the structural shocks, computed as $\varepsilon_t = A^{-1}u_t$, in addition to the impulse responses. The reason for this is that in sections 4.4.2 and 4.4.3 I impose restrictions on the shock series themselves and thus all of the structural shock series are needed. Specifically, for each model I search for a shock series that behaves in accordance with the boom-bust episode of the late 1990's and early 2000's and given that such a shock exists it is identified as an IST news shock.

The next three sections will present results from the three identification schemes discussed above all of which are aimed at forming the set of theory-consistent models from the set of models generated by the above algorithm.

4.4.1 Exploiting the Basu et al. (2010) Results

As a first way to tackle the issue of distinguishing between IST news shocks and unanticipated IST shocks, I utilize information from Basu et al. (2010). The latter paper used input-output tables and industry specific technology innovations to identify unanticipated IST shocks which are robust to a possible wedge between RPI and IST and found that unanticipated IST shocks generate a decline in output, hours, investment, and consumption on impact. Hence, I keep models in which 98% of the long-run variation in RPI is driven by twos shocks, one of which generates an impact decline in the real aggregates and is accordingly identified as the unanticipated IST shock where the other shock is identified as the IST news shock.

Figures 11a-12b provide the equivalent type of information on the set of the theory-consistent models as did figures 1-4 only that now the latter set is generated in accordance with the above framework rather than the benchmark framework. The figures are based on 1,000,000 randomly generated models from which a total of 624 theory-consistent models were collected. The latter figures demonstrate that IST news shocks generate business cycle comovement and drive the bulk of the business cycle variation in output, hours, and investment. Moreover, these shocks are the major force behind the long-run variation in IST.[19] The median contribution to the two year variation

[19] Note that even though RPI and IST are not assumed to be equal, it can still be deduced that IST news shocks are the main driver of the long run variation in IST directly from knowing that they are the main driver of that in RPI. The reason for this is that unanticipated IST shocks and IST news shocks are the

in output, hours, investment, and consumption are 59%, 67%, 60%, and 35%, respectively. Note that the contribution to consumption variation is quite weaker relative to the benchmark estimate. Interestingly, this is in part accounted for by a significant contribution of the unanticipated shock, which has a median contribution to consumption variation of 37%.[20] Nevertheless, the results for the other variables are quantitatively similar to the benchmark ones and are similar to the benchmark results with respect to output. Moreover, although IST news shocks explain less of the variation in consumption relative to the benchmark case, they still significantly raise consumption on impact with a median impact effect of 0.26%. Lastly, note that endogenizing RPI doesn't change by much the evolution of RPI following the IST news shock compared to the benchmark case. Specifically, RPI doesn't move by much on impact but rather experiences a gradual and persistent change.

4.4.2 Exploiting the late 1990's and Subsequent early 2000's Boom-Bust Episode

The common view by economists is that the late 1990's boom and subsequent bust were generally related to overly optimistic expectations regarding information technology that were followed by a downward revision of these expectations (e.g. Beaudry and Portier (2004), Jaimovich and Rebelo (2009), and Karnizova (2012)).[21] Hence, a sensible way in which one can try to distinguish between IST news shocks and unanticipated IST shocks is to impose the restriction that one of the two shocks had significant positive realizations in the late 1990's followed by negative ones in the early 2000's. Towards that end, I keep models in which 98% of the long-run variation in RPI is driven by twos shocks, one of which exhibits the maximal three year moving average in the period of 1997:Q1-1999:Q4 and a negative mean in the subsequent 2000:Q1-2002:Q4 period that is at least 25% in absolute value of the mean of the 1997:Q1-1999:Q4 sub-series. This implies that the sum of the

sole two sources of the unit root in IST and hence in RPI as well, thus implying that if IST news shocks are the major force behind the long run variation in RPI they must also be the major force behind the long-run variation in IST.

[20] The median contributions of the unanticipated shock to the two year variation in output, hours, and investment are 22%, 19%, and 13%, respectively. Moreover, the median effect of the unanticipated shock on the latter variables as well as on consumption is positive. These results are available upon request from the author.

[21] 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 information technology.

negative series is at least 25% of that of the positive series, thus indicating that at least a 25% correction of the overly optimistic expectations of the late 1990's takes place in the early 2000's.[22]

The shock that behaves in accordance with the latter boom-bust restrictions is naturally identified as the IST news shock. Note that the requirement that the mean of the 1997:Q1-1999:Q4 shock sub-series is the maximal among all other three year moving averages in the series allows me to avoid imposing any restrictions on the absolute magnitude of the shocks, which is hard to do given the lack of information on the absolute size of the shocks that that were realized in this period, but rather only rely on the observation that this period is the most apparent boom period related to optimistic IST news shocks in the sample. Moreover, the additional restriction on the mean of the 2000:Q1-2002:Q4 sub-series being such that the correction of expectations amounts to at least 25% of the boom years is quite weak given that stock prices essentially gave up all of the gains realized in the late 1990's boom period during the bust period.

Figures 13a-14b provide the equivalent type of information on the set of the theory-consistent models as did figures 1-4 only that now the latter set is generated in accordance with the above framework rather than the benchmark framework.[23] The figures are based on 1,000,000 randomly generated models from which a total of 1815 theory-consistent models were collected. It is apparent that the main features of the results are unchanged as IST news shocks are still the main driver behind the business cycle variation in the real aggregates and generate business cycle comovement. The 10th percentile impact effects of IST news shocks on output, hours, investment, and consumption are 0.33%, 0.21%, 0.94%, and 0.26%, respectively, while the median impact effects are 0.48%, 0.33%, 1.55%, and 0.33%, respectively. All of the latter effects are economically significant and point to the strong business cycle comovement that the IST news shock generates. The 10th percentile contributions of IST news shocks to output, hours, investment and consumption at the two year horizon are 51%, 59%, 45%, and 40%, respectively, while the median contributions are 72%,

[22]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.

[23]The responses of the real aggregates to unanticipated IST shocks were found to be quite ambiguous. Nevertheless, the median responses were positive for output, investment, and hours, and essentially zero for consumption. The median contributions to the business cycle variation of the real aggregates were low, failing to exceed 5% for output, consumption, and hours and only reaching 10% for investment. So as to save on space, the results on the unanticipated IST shocks are not presented and are available upon request from the author.

79%, 67%, and 63%, respectively. Moreover, in consistence with the benchmark case, the median contributions to the long-run variation in output and consumption are similar to their business cycle counterparts whereas for investment the long-run contribution is lower at 22%. Lastly, IST news shocks continue to be the main driver behind RPI variation with the median contribution at 91%.

4.4.3 Relaxing the Long-Run Restriction

One concern that may arise given the results from the previous two section is that other shocks may still affect RPI in the long run thereby rendering the imposed long-run restrictions potentially invalid. Hence, I will now present results obtained from relaxing the long-run restriction and merely relying on the restriction that the identified shock series behaves in accordance with the late 1990's and early 2000's boom-bust period. In particular, I now allow all shocks to freely affect RPI at *all* horizons, including the long-run horizon, and require the boom-bust restriction from section 4.4.2, i.e. that the identified shock exhibit the maximal three year moving average in the period of 1997:Q1-1999:Q4 and a negative mean in the subsequent 2000:Q1-2002:Q4 period that is at least 25% in absolute value of the mean of the 1997:Q1-1999:Q4 sub-series. This implies that the sum of the negative series is at least 25% of that of the positive series, thus indicating that at least a 25% correction of the overly optimistic expectations of the late 1990's takes place in the early 2000's.

Figures 15a-16b provide the equivalent type of information on the set of the theory-consistent models as did figures 1-4 only that now the latter set is generated in accordance with the above framework rather than the benchmark framework. The figures are based on 1,000,000 randomly generated models from which a total of 27,294 theory-consistent models were collected. It is apparent that the main results are maintained even in this unrestrictive framework as favorable IST news shocks raise the real aggregates and account for the majority of their business cycle variation. The median impact effects on output, hours, investment, and consumption are 0.44%, 0.30%, 1.39%, and 0.32%, respectively, while the median contributions to their two year variation are 65%, 69%, 59%, and 62%, respectively. It is encouraging that even in this unrestrictive framework in which RPI is completely endogenous also in the long run in addition to the short and medium run, the boom-bust restriction is sufficient to identify the IST news shocks and generate strong results.

The exercises conducted in this section as well as the previous one demonstrate that identification strategies that rely on information regarding particular time periods 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.

5 Conclusion

This paper has put forward a new VAR-based approach to the identification of news shocks. The approach is related to the sign restrictions SVAR literature in that it generates a set of models that are consistent with the basic assumption in news driven models that technology is driven by two shocks, one being the unanticipated technology shock and the other being the technology news shocks. The method has three main advantages. First, as demonstrated by Canova and Paustian (2011), methods based on sign restrictions can be quite informative about the true data process. Second, the case of news shocks is particularly appealing for employing methods that are based on the sign restrictions approach given given that these shocks introduce a set of restrictions that are common across news driven models. That the implied restrictions implied by news shocks are model-based robust restrictions is important and renders the proposed method suitable for identifying news shocks. Lastly, in contrast to previous papers which identified news shocks via point identification methods (e.g. Beaudry and Portier (2006), Beaudry and Lucke (2010), Barsky and Sims (2011), and Ben Zeev and Khan (2012)), my proposed method accounts for both identification uncertainty and parameter uncertainty, whereas previous methods only accounted for the latter.

The method is applied on IST and is found to be very informative about the true data generating process. Specifically, I find that favorable IST news shocks raise the real aggregates on impact and are the major force behind their business cycle variation. Moreover, these shocks account for the bulk of the long-run variation in IST. Overall, the results of this paper constitute a challenge to builders of macroeconomic models as current DSGE models lack the ingredients with which IST news shocks can be the major force behind the business cycle. Moreover, the finding that IST news shocks are the major force behind the long-run variation in output in addition to its business cycle variation is consistent with the view that IST is a central variable in macroeconomics both in the short run as well as the long run (e.g. Greenwood et al. (1997, 2000))). The main novelty of this paper's results is that the driver of the latter view is the news component of IST, rather than the unanticipated component.

Furthermore, I demonstrated in sections 4.4.2 and 4.4.3 that identification strategies that rely on information regarding particular time periods 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 themselves. An interesting avenue of research to explore, which I have recently embarked on, is trying to exploit the information we have on the recent financial crisis to identify credit supply shocks.

Appendix A Posterior Distribution of Reduced Form VAR Parameters

The VAR given by (3) 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:

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

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

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:

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

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

where $v_T = T + v_0,\ N_T = N_0 + X'X,\ \bar{B}_T = N_T^{-1}(N_0\bar{B}_0 + X'X\hat{B}),$
$S_T = \frac{v_0}{v_T}S_0 + \frac{T}{v_T}\hat{\Sigma} + \frac{1}{v_T}(\hat{B} - \bar{B}_0)'N_0N_T^{-1}X'X(\hat{B} - \bar{B}_0),\ \hat{B} = (X'X)^{-1}X'Y,$
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.

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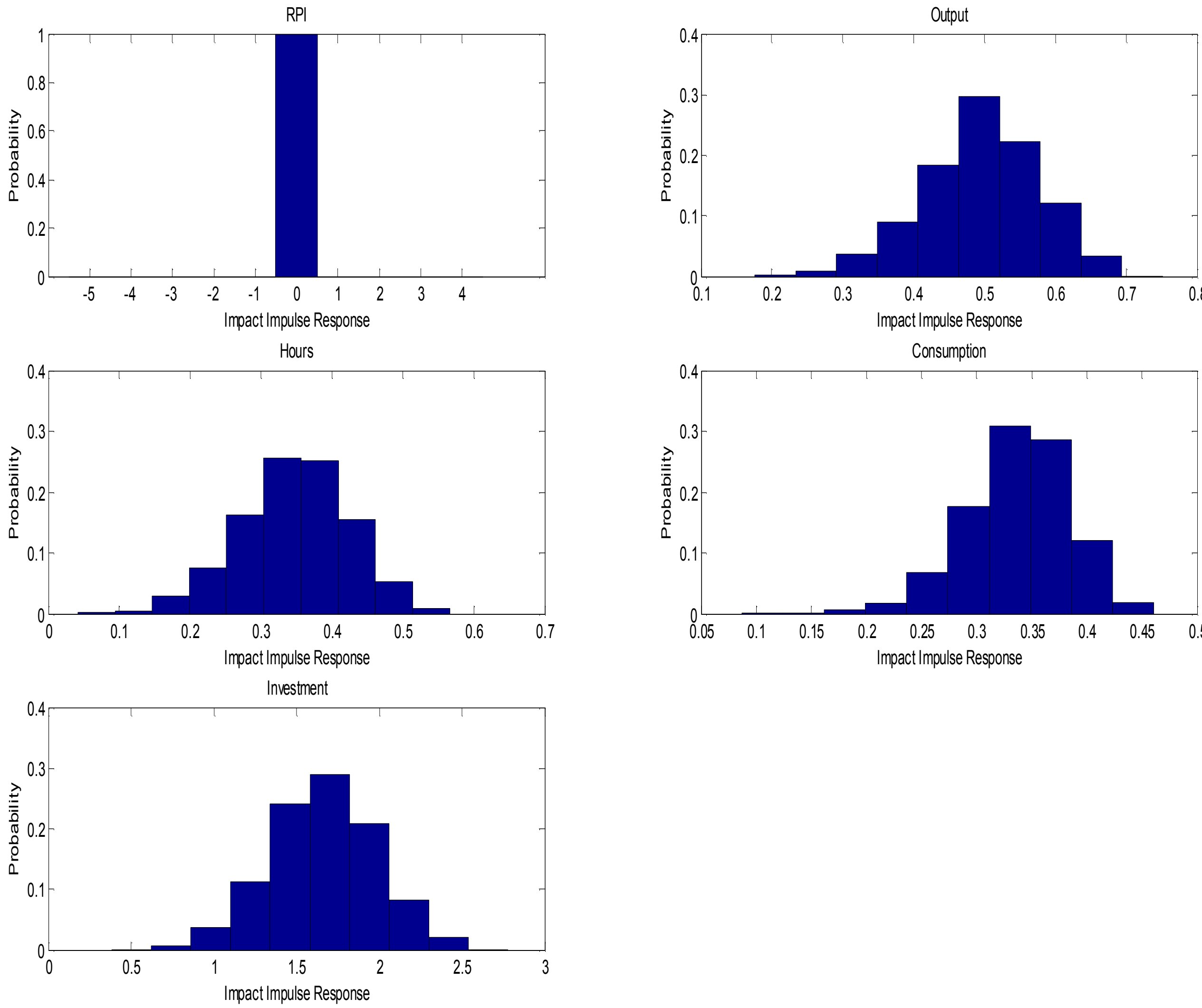
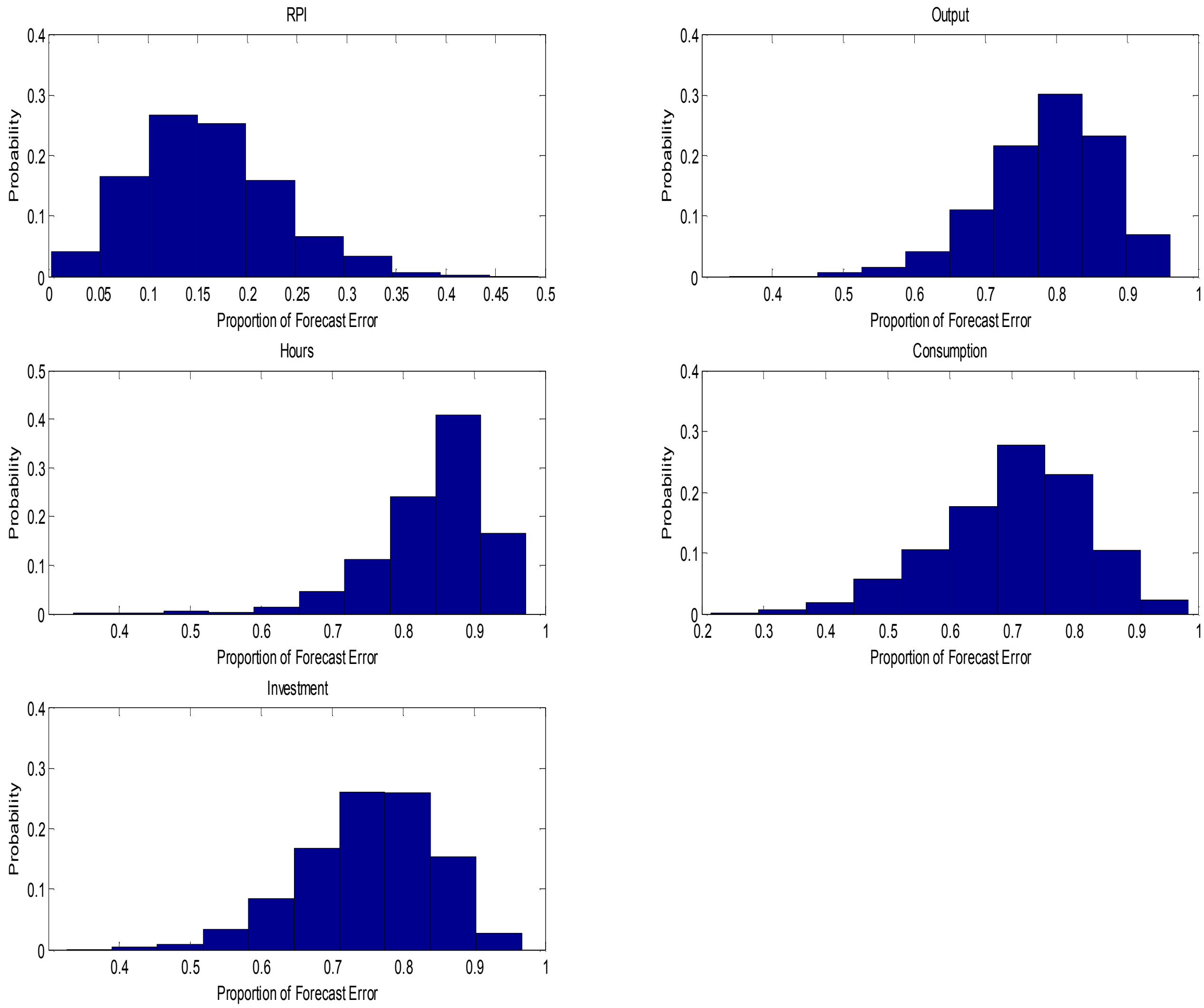
Figure 1: **Normalized Histogram of Impact Impulse Responses to an IST News Shock (Benchmark Case)**.



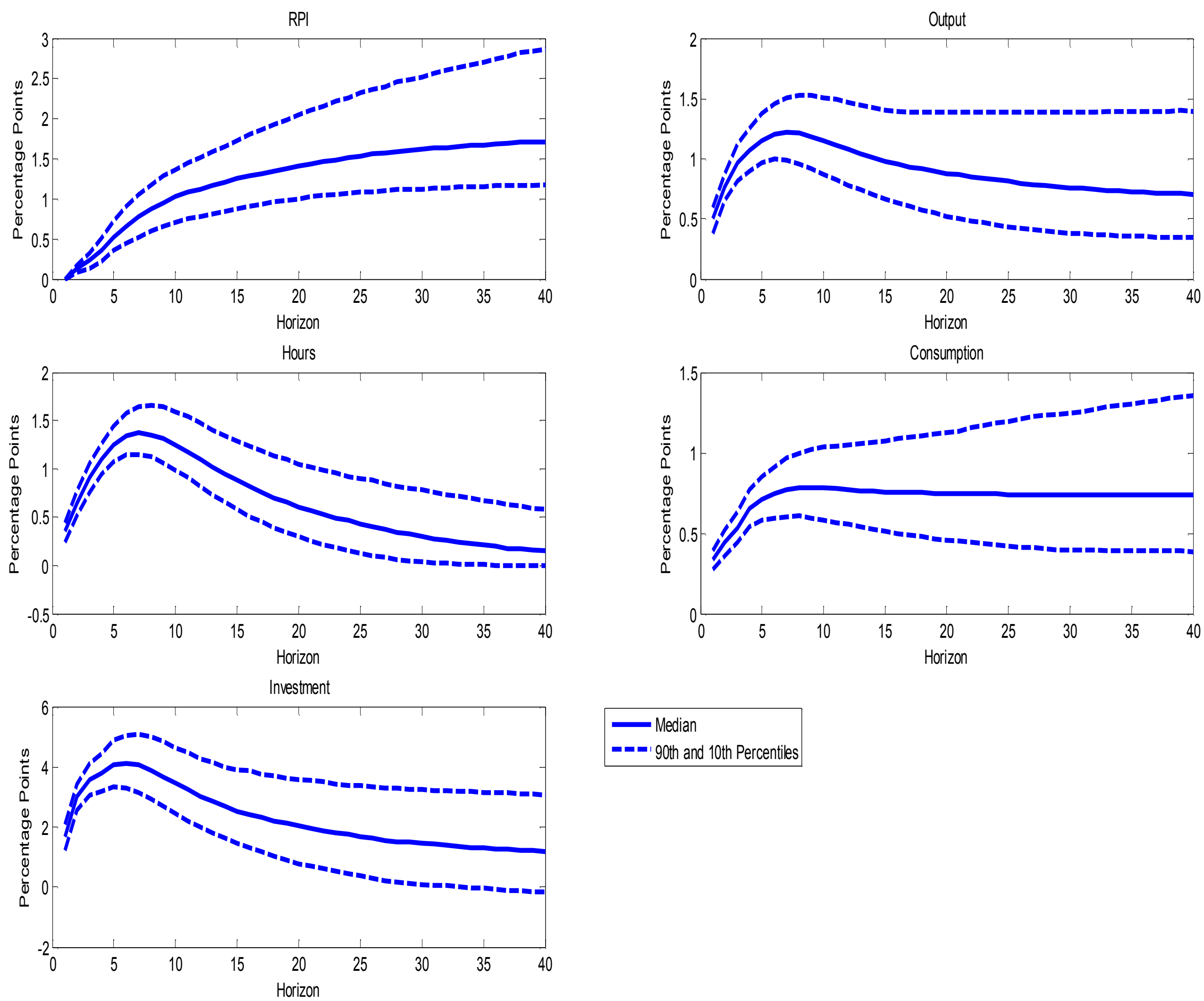
Notes: This figure presents the posterior distribution of the impact impulse responses to an IST news shock. In this figure, as well as all of the next figures, it was ensured that the identified IST news shock is a favorable shock by multiplying the impulse responses by -1 if the the long-run effect of the shock on RPI was negative.

Figure 2: **Normalized Histogram of the Contribution of IST News Shocks to the Forecast Error Variance of the Variables at the Two Year Horizon (Benchmark Case)**.



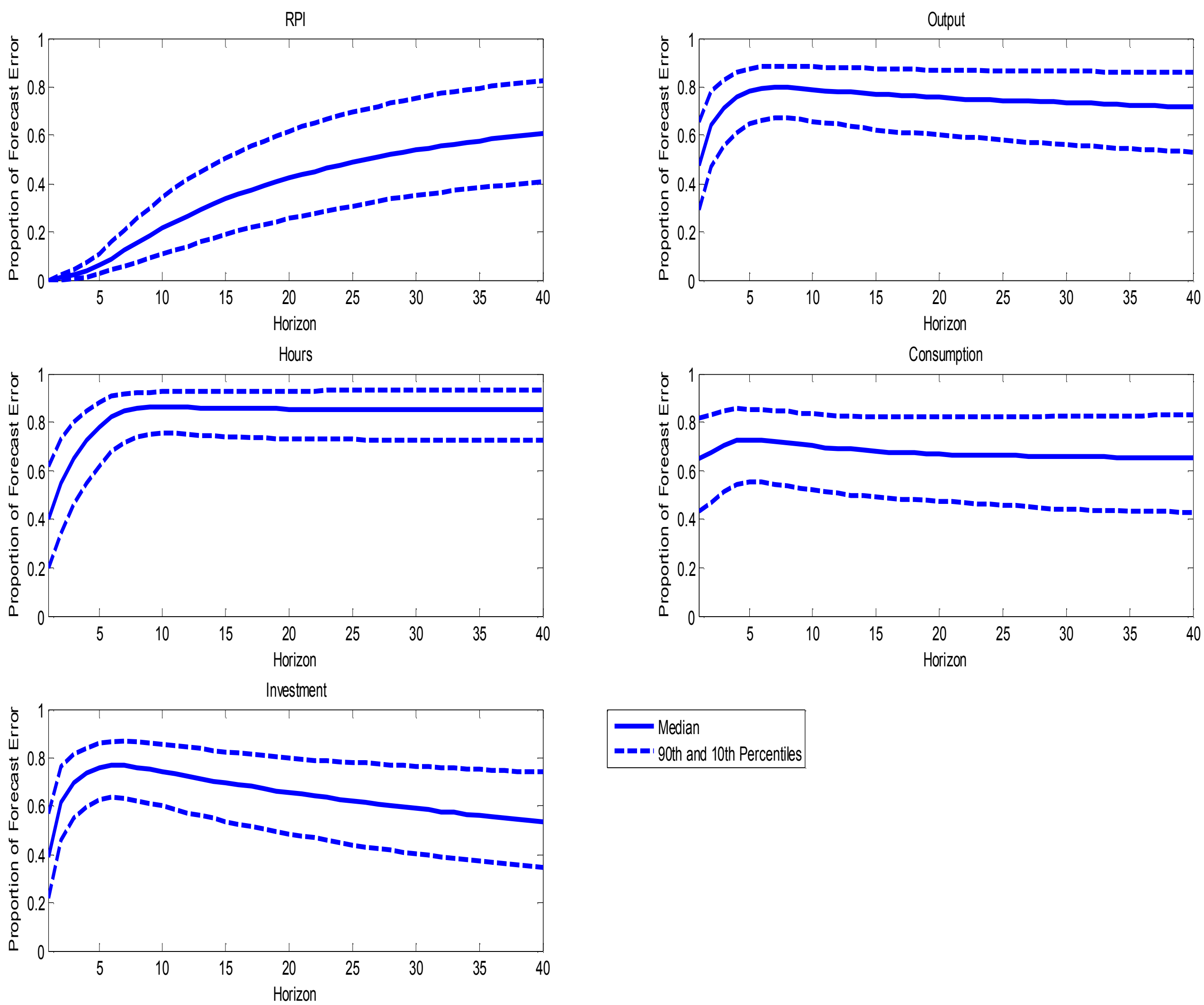
Notes: This figure presents the posterior distribution of the contribution of the IST news shock to the forecast error variance of the variables at the two year horizon.

Figure 3: **The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks (Benchmark Case)**.



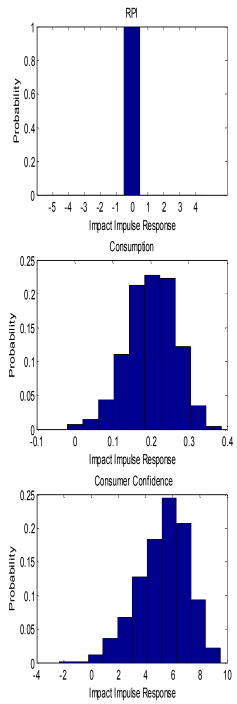
Notes: The solid line is the median impulse response and the dashed lines are the 90th and 10th percentiles of the posterior distributions of impulse responses.

Figure 4: **The Median and 90th and 10th percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables (Benchmark Case).**

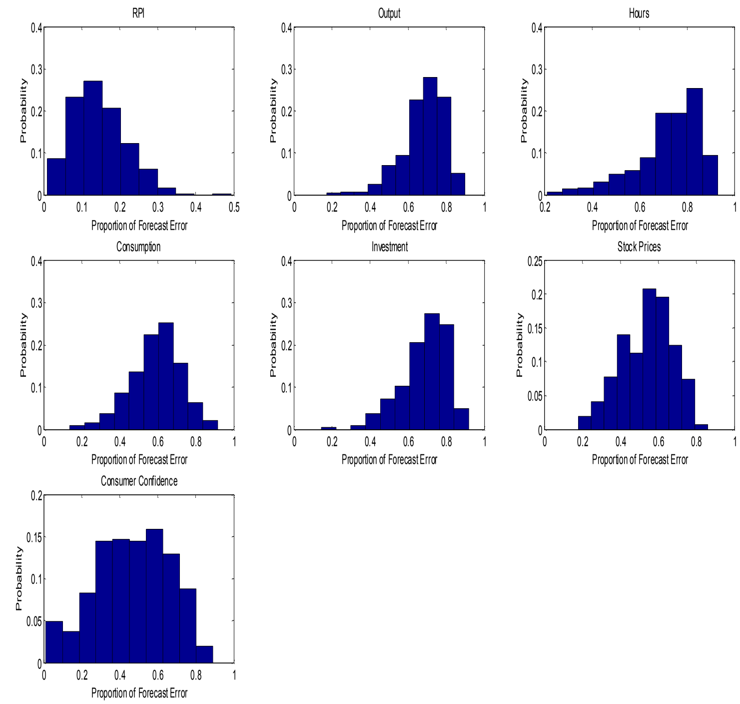


Notes: The solid line is the median contribution and the dashed lines are the 90th and 10th percentiles of the posterior distribution of contributions.

Figure 5: **Larger VAR: (a) Impact Response Histogram; (b) Two Year FEV Histogram**



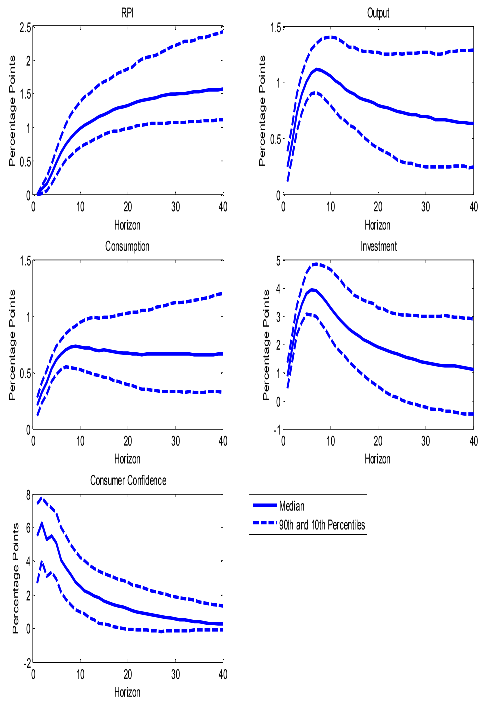
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



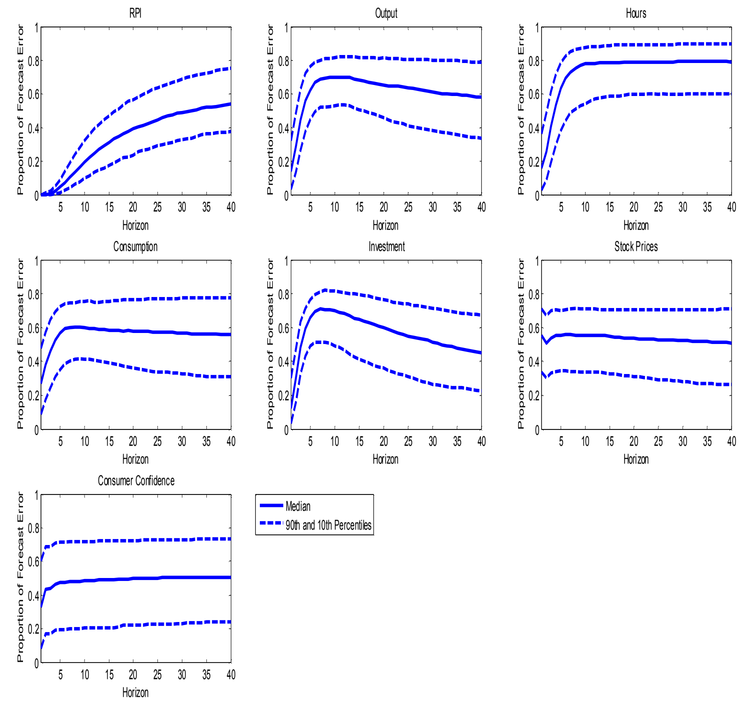
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from a VAR that includes stock prices and consumer confidence). 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 and consumer confidence).

Figure 6: **Larger VAR: (a) Impulse Responses ; (b) Contribution to FEV**



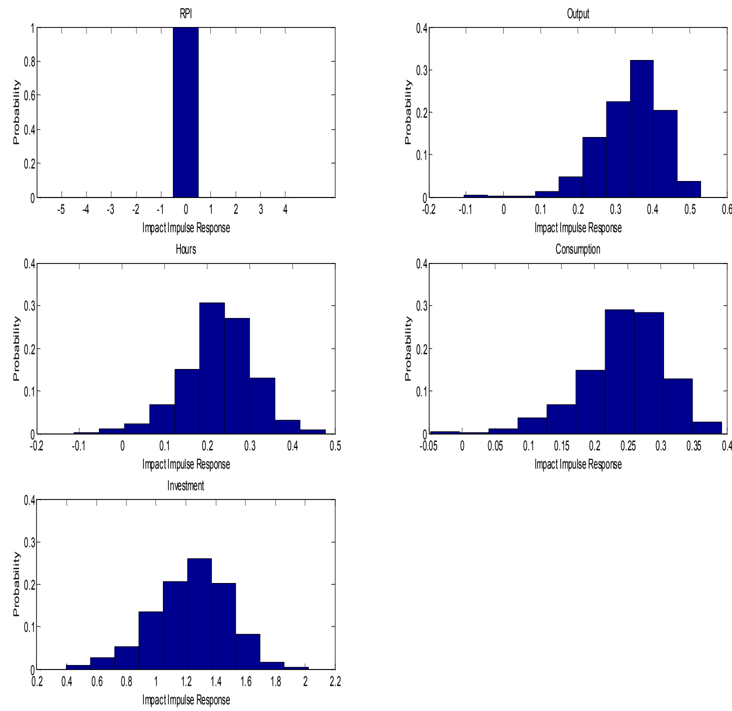
(a) The Median and 90th and 10th percentiles of the Impulse Responses to IST News Shocks.



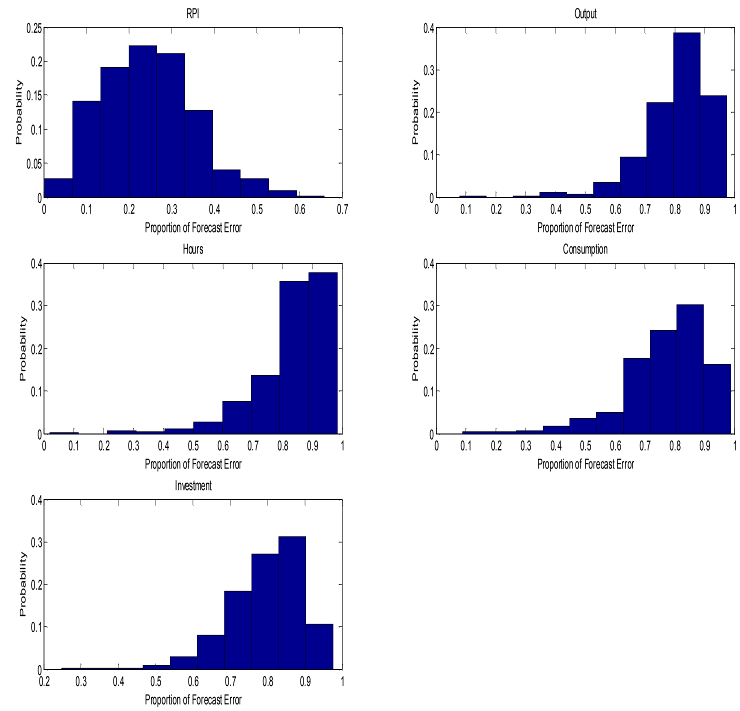
(b) The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.

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 a VAR that includes stock prices and consumer confidence). 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 and consumer confidence).

Figure 7: **Post 1982 Sample: (a) Impact Response Histogram; (b) Two Year FEV Histogram**



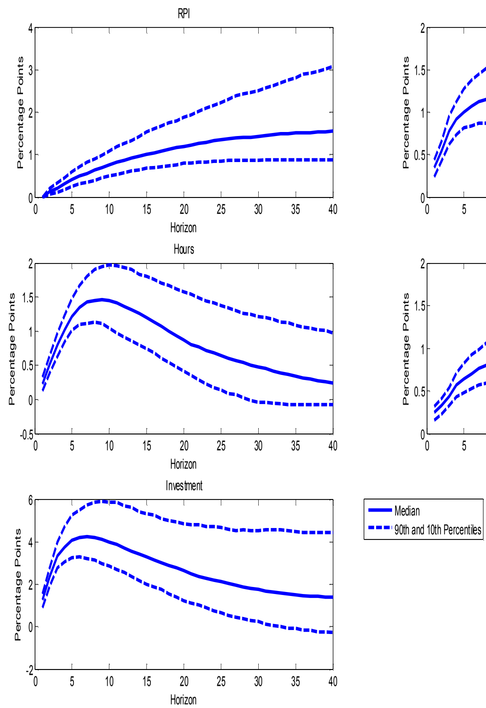
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



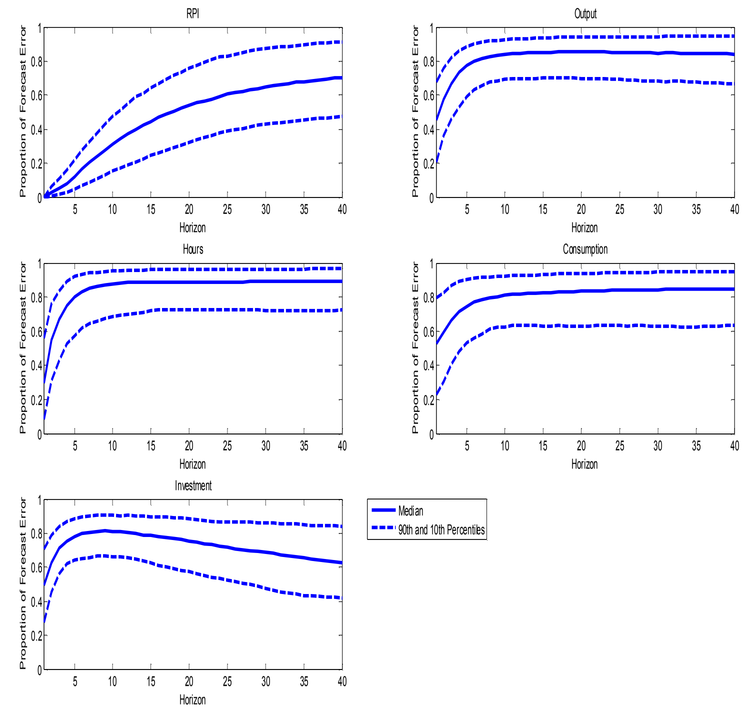
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from a 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 8: **Post 1982 Sample: (a) Impulse Responses ; (b) Contribution to FEV**



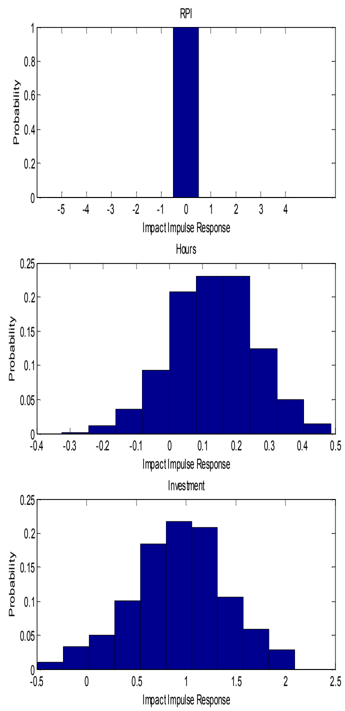
(a) The Median and 90th and 10th Percentiles of the Impulse Responses to IST News Shocks.



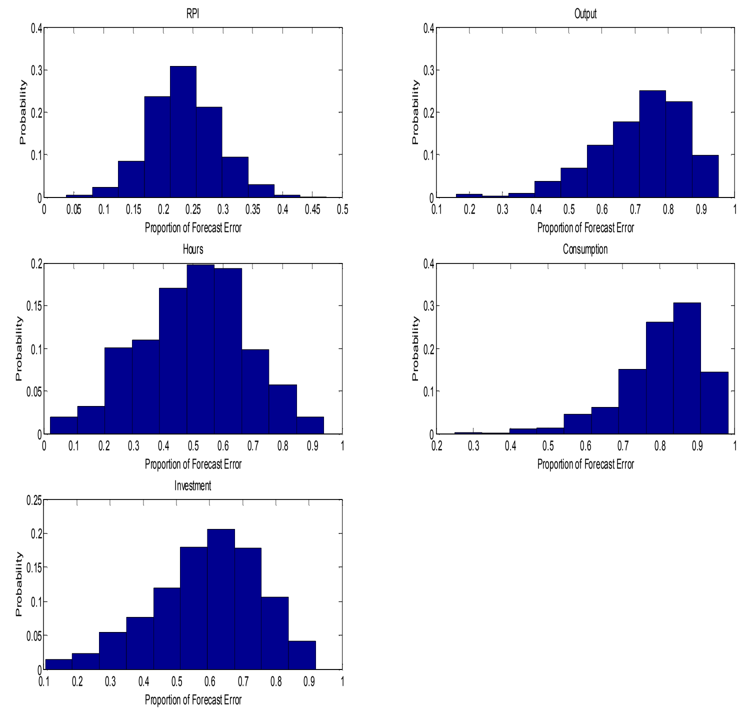
(b) The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.

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 9: **Non-Stationary Hours: (a) Impact Response Histogram; (b) Two Year FEV Histogram**



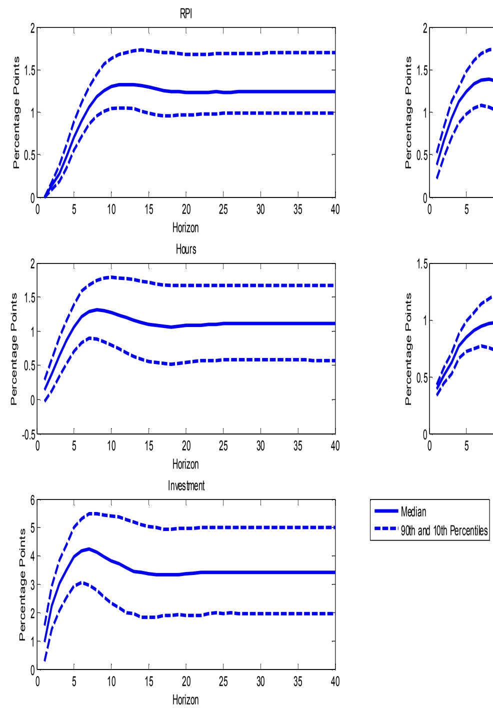
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



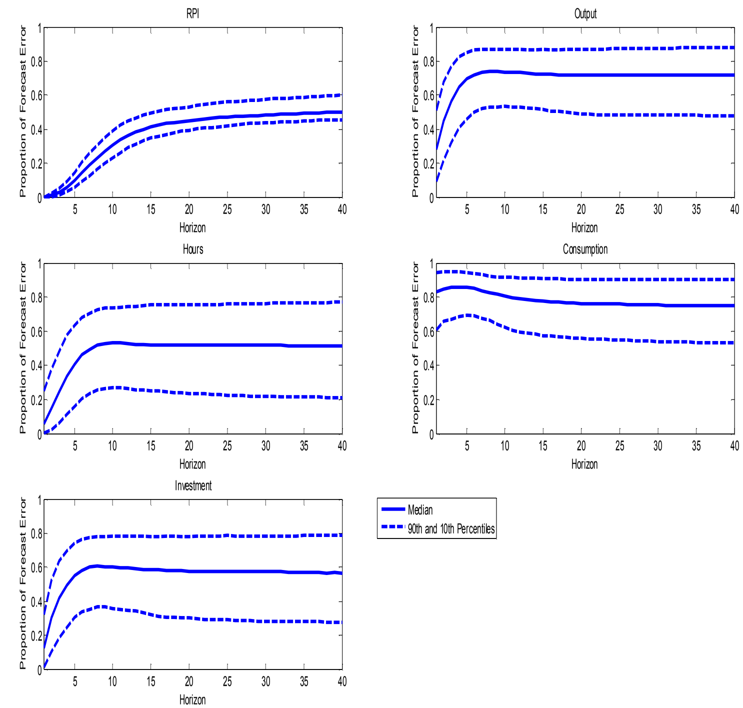
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (obtained from 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 10: **Non-Stationary Hours: (a) Impulse Responses ; (b) Contribution to FEV**



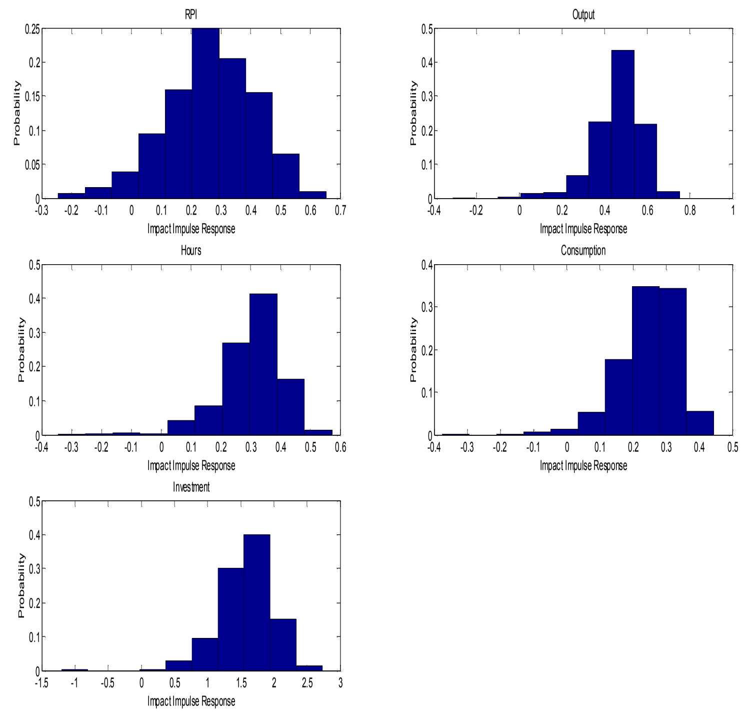
(a) The Median and 90th and 10th Percentiles of the Impulse Responses to IST News Shocks.



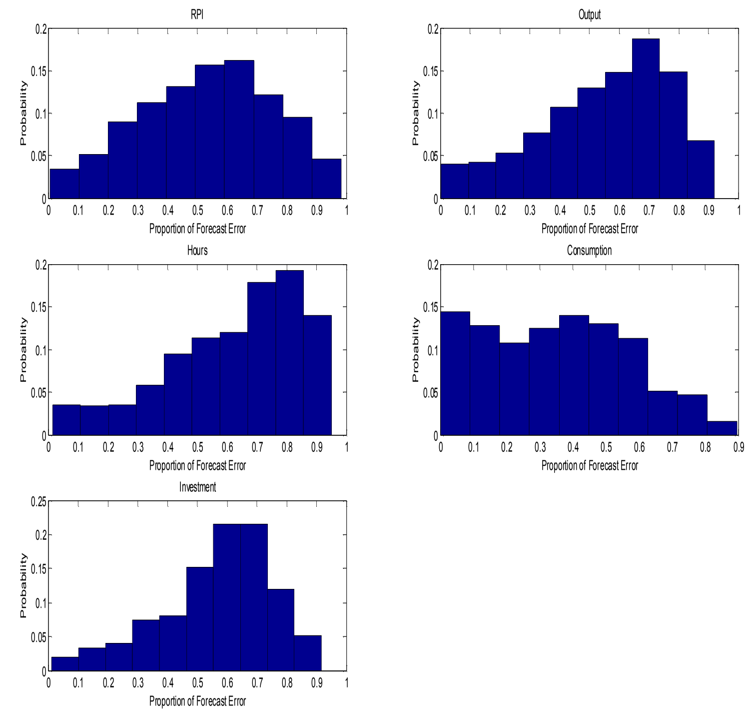
(b) The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.

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 11: **Endogenous RPI (Exploiting the Basu et al. (2010) Results): (a) Impact Response Histogram; (b) Two Year FEV Histogram**



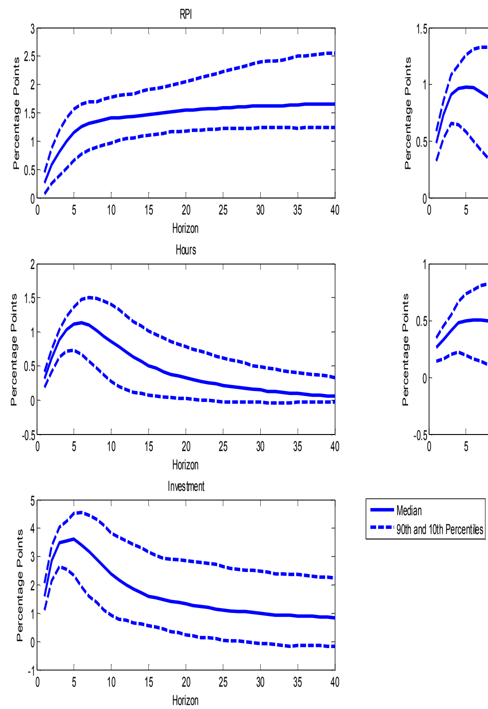
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



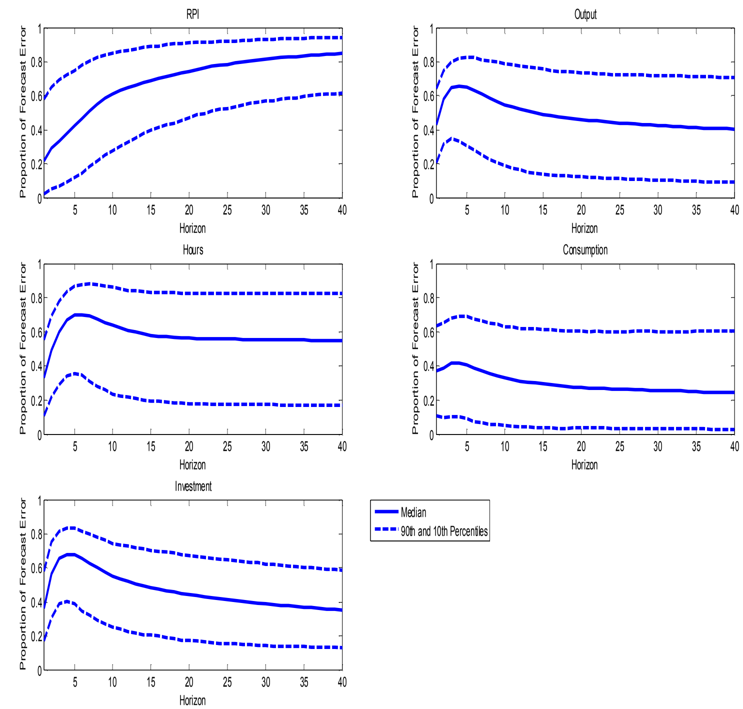
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: The results of this figure are based on the assumption that IST is the sole source of the unit root in RPI and that unanticipated IST shocks reduce the real aggregates, as found by Basu et al. (2010). Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).

Figure 12: **Endogenous RPI (Exploiting the Basu et al. (2010) Results): (a) Impulse Responses ; (b) Contribution to FEV**



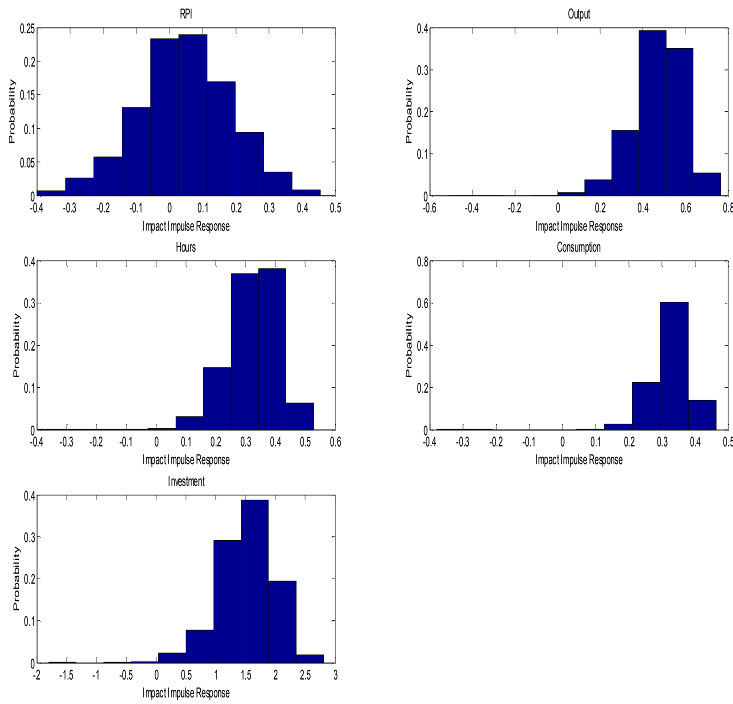
(a) The Median and 90th and 10th Percentiles of the Impulse Responses to IST News Shocks.



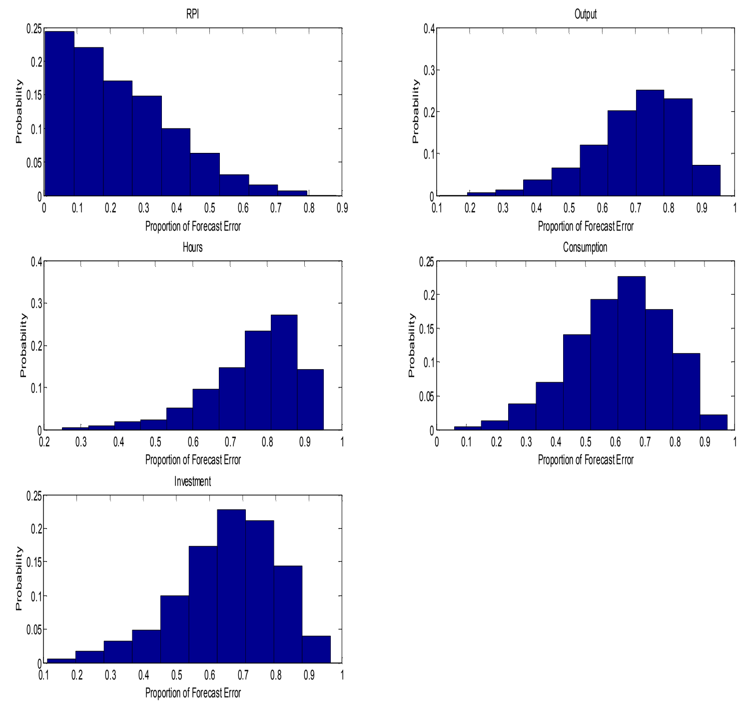
(b) The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.

Notes: The results of this figure are based on the assumption that IST is the sole source of the unit root in RPI and that unanticipated IST shocks reduce the real aggregates, as found by Basu et al. (2010). 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 (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).

Figure 13: **Endogenous RPI (Exploiting the 1997-2002 Boom-Bust Period): (a) Impact Response Histogram; (b) Two Year FEV Histogram**



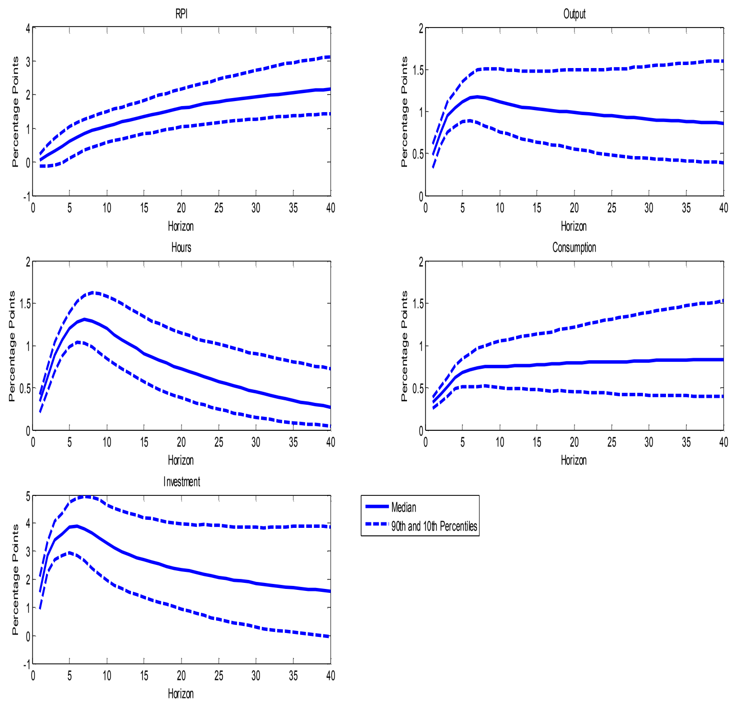
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



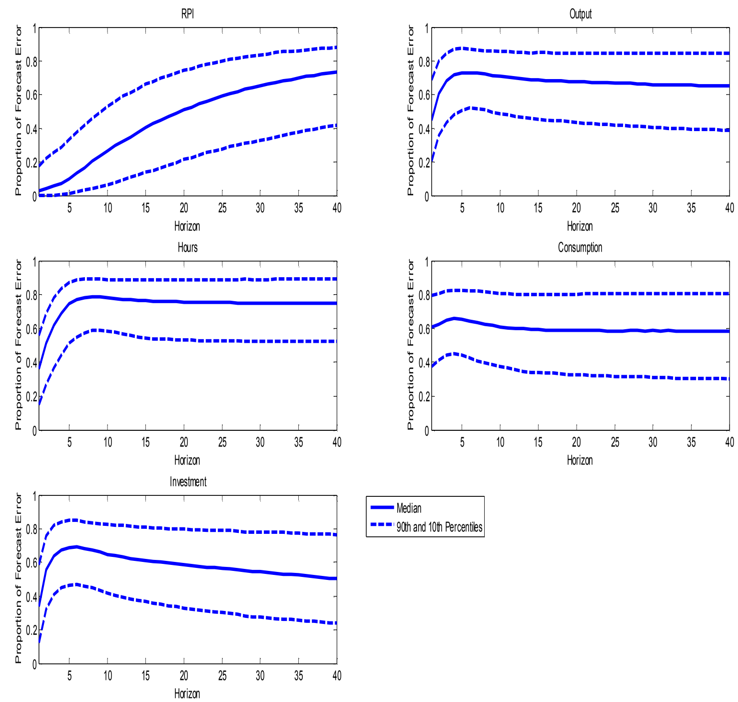
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: The results of this figure are based on the assumption that IST is the sole source of the unit root in RPI and that IST news shocks behave in accordance with the boom-bust 1997-2002 period. Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).

Figure 14: **Endogenous RPI (Exploiting the 1997-2002 Boom-Bust Period): (a) Impulse Responses ; (b) Contribution to FEV**



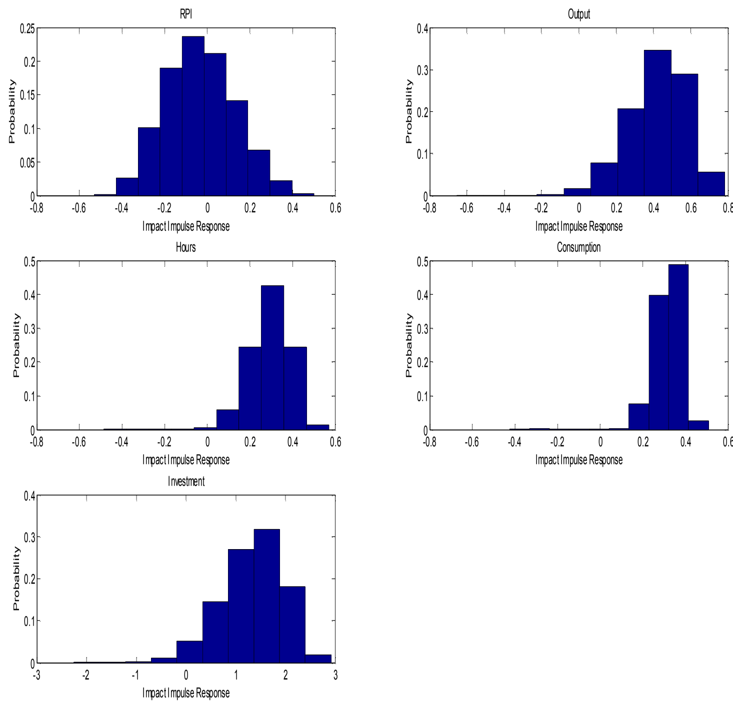
(a) The Median and 90th and 10th Percentiles of the Impulse Responses to IST News Shocks.



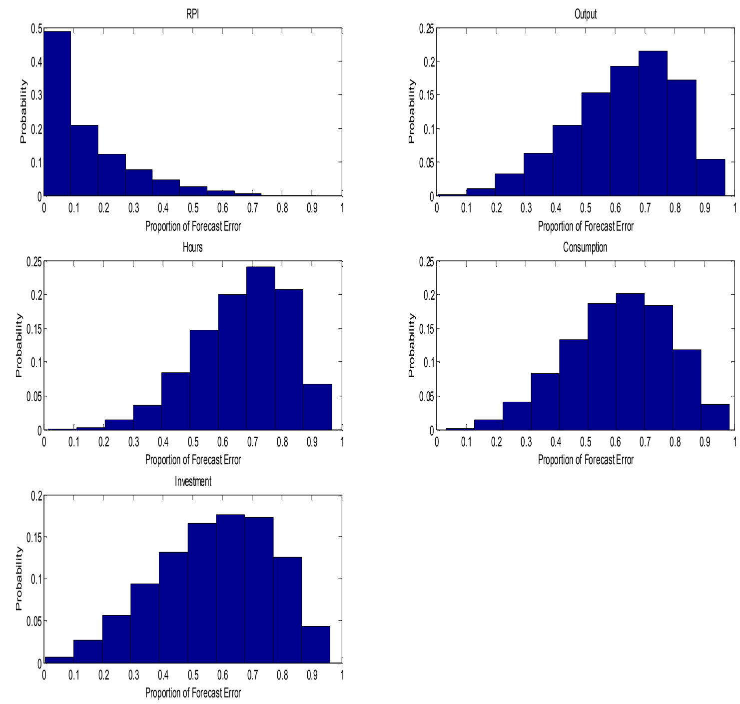
(b) The Median and 90th and 10th Percentiles of the Contribution of IST News Shock to Forecast Error Variance of the Variables.

Notes: The results of this figure are based on the assumption that IST is the sole source of the unit root in RPI and that IST news shocks behave in accordance with the boom-bust 1997-2002 period. 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 (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).

Figure 15: **Endogenous RPI (Relaxing the Long-Run Restriction): (a) Impact Response Histogram; (b) Two Year FEV Histogram**



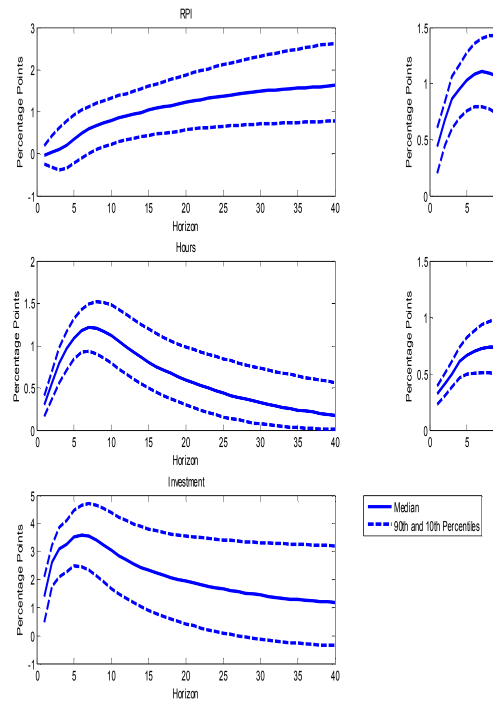
(a) Normalized Histogram of Impact Impulse Responses to an IST News Shock.



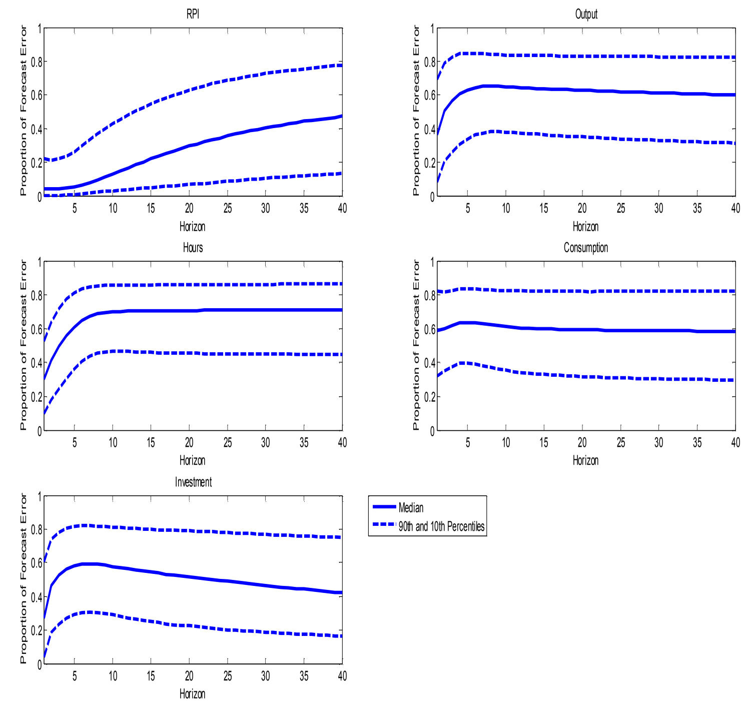
(b) Normalized Histogram of Contribution of IST News Shock to Forecast Error Variance of the Variables at the Two Year Horizon.

Notes: The results of this figure are based on the assumption that IST news shocks behave in accordance with the boom-bust 1997-2002 period. Panel (a): This figure presents the posterior distribution of the impact impulse responses to an IST news shock (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).

Figure 16: **Endogenous RPI (Relaxing the Long-Run Restriction): (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: The results of this figure are solely based on the assumption that IST news shocks behave in accordance with the boom-bust 1997-2002 period. 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 (allowing for a wedge between RPI and IST). 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 (allowing for a wedge between RPI and IST).