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Nadav Ben Zeev
European University Institute

Hashmat Khan
Carleton University

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Carleton UNIVERSITY

Department of Economics

1125 Colonel By Drive
Ottawa, Ontario, Canada
K1S 5B6

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Nadav Ben Zeev†
European University Institute

Hashmat Khan‡
Carleton University

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Abstract

This paper provides robust evidence that news shocks about future investment-specific technology (IST) constitute a significant force behind U.S. business cycles. Using a recent empirical approach to identifying news shocks, we find that positive IST news shocks induce comovement, i.e., raise output, consumption, investment, and hours. These shocks account for 70% of the business cycle variation in output, hours, and consumption, and 60% of the variation in investment, and have played an important role in nine of the last ten U.S recessions. IST news shocks also dominate unanticipated IST shocks in accounting for the forecast variance of aggregate variables. The findings have two important implications for research on news driven business cycles. First, they provide strong support for shifting focus to IST news shocks when investigating the role of news (or foresight) in driving business cycles. Second, an important avenue for further research is to consider structural mechanisms that can enhance the role of IST news shocks in estimated dynamic general equilibrium models.

JEL classification: E32

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†Department of Economics, Ben-Gurion University of the Negev, Beer-Sheva, Israel. *E-mail:* nadavbz@bgu.ac.il.

‡Department of Economics, Carleton University, Ottawa, Canada. *E-mail:* hashmat.khan@carleton.ca.

1 Introduction

Following Beaudry and Portier (2006), recent empirical research has focused on shocks to future fundamentals as the driving force behind business cycles. Thus far, future total factor productivity (TFP) has been considered the main variable of interest in the VAR-based approaches to identify news shocks.[1] Beaudry and Portier (2006) and Beaudry and Lucke (2010), using a combination of short-and long-run restrictions, find that TFP news shocks generate comovement among macroeconomic variables, and account for over two-thirds of the U.S. business cycle fluctuations in hours and output. By contrast, Barsky and Sims (2011), using a relatively advantageous identification method based on the maximum forecast error variance approach, find that positive TFP news shocks fail to produce comovement on impact, and that they do not account for output declines in four out of six U.S. recessions between 1961 and 2007.

In this paper we consider news shocks to a different future fundamental relative to the above mentioned research, namely, investment-specific technology (IST). Our main contribution is to identify IST news shocks and quantify their role in post-WWII U.S. business cycles. We focus on IST for two reasons. First, a large body of literature has considered its relevance for growth, business cycles, and asset prices (Greenwood et al. (1988), Greenwood et al. (1997), Greenwood et al. (2000), Papanikolaou (2011)). Fisher (2006) identified unanticipated IST shocks using data on the real price of investment, and found that they have accounted for over two-thirds of business cycle fluctuations in output over the 1982-2000 period. Since the previous focus has been on unanticipated IST shocks, the relative importance of identified IST news shocks has not yet been determined. Second, IST news shocks have been introduced in the DSGE literature (see, for example, Davis (2007), Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), and Khan and Tsoukalas (2012)), but they have not yet been identified in the data using the VAR methodology, which has the advantage that it imposes minimal restrictions to identify shocks. It is, therefore, an open question whether the quantitative effects of IST news shocks in the DSGE models are consistent with those in the data identified via a VAR-based approach.

[1] Previously, the empirical findings of Galí (1999), Francis and Ramey (2005), Basu et al. (2006), and Fernald (2007) suggested that unanticipated aggregate productivity shocks are unlikely to be a major source of business cycles.

Our benchmark measure of IST is the inverse of the real price of investment.[2] We consider the maximum forecast error variance (MFEV) identification approach proposed by Barsky and Sims (2011) to identify IST news shocks using U.S. data over the period 1951:Q1 to 2012:Q1. Barsky and Sims (2011) identified TFP news shocks as the shocks that maximally explain future variation in TFP over a finite horizon orthogonalized with respect to current TFP. This identification requires adding one identifying restriction to the MFEV optimization problem. We add two restrictions to identify IST news shocks. In particular, the IST news shock is identified as the linear combination of reduced form innovations orthogonal to *both* current TFP and current IST which maximizes the sum of contributions to IST forecast error variance over a finite horizon. These restrictions are based on the assumptions that (i) only a limited number of shocks affect IST and (ii) the IST news shocks do not affect IST contemporaneously but rather foretell future changes in it. A key advantage of the MFEV approach is that unlike the long-run restrictions approach, it does not rely on the precise assumptions about the stochastic trend in the variable of interest (which can be a matter of debate) or the number of common stochastic trends among the variables of interest (which can affect inference).

There are three key findings. First, IST news shocks induce positive business cycle comovement, i.e., a positive IST news shock raises output, consumption, investment, and hours. This comovement is a key property of observed business cycle. Second, IST news shocks account for 70% of the business cycle variation in output, hours, and consumption, and 60% of the variation in investment. These large quantitative contributions imply that IST news shocks are a dominant source of U.S. business cycles. Third, the relevance of IST news shocks is further emphasized in terms of their role in the past recessions in the U.S. economy. We find that IST news shocks account for a significant share of the output per capita loss in nine of the last ten U.S. recessions. Overall, our findings indicate that IST news shocks are not only capable of generating business cycles but also that they have played an important role as drivers of U.S business cycles over the last sixty years.

Fisher (2006) identified unanticipated IST shocks in an SVAR framework using long-run restrictions and found that IST shocks are important drivers of the business cycle. **However, we**

[2]As shown in Greenwood et al. (2000), this inverse relationship between IST and the real price of investment can be derived in either a one sector model or a two sector model with consumption and investment sectors.

find that when both unanticipated IST and IST news shocks are identified, where the unanticipated shock is identified as the innovation in IST orthogonalized with respect to TFP, two new findings emerge. First, the correlations between the unanticipated IST shocks identified using Fisher's long-run restrictions and the unanticipated IST and IST news shocks identified using our approach are 0.37 and 0.78, respectively. These correlations suggest that the unanticipated IST shocks identified in Fisher (2006) are a combination of both unanticipated IST and IST news shocks, and that they are more strongly associated with the IST news shocks than with unanticipated IST shocks **that we obtain**. Second, IST news shocks dominate unanticipated IST shocks in terms of their contributions to the forecast error variances of output, consumption, hours, and investment.

Our benchmark VAR specification includes nine variables, namely, TFP, IST, nominal interest rate, inflation, GDP, investment, consumption, total hours, and credit spread. Following a positive IST news shock the credit spread declines in a hump shaped manner, falling by 7 basis points after 5 quarters. The IST news shocks account for about 20% of the credit spread variation, suggesting that some of the predictive power of the spread is due to IST news. Moreover, since output rises, the countercyclical credit spread suggests that financial markets may play a role in the propagation of IST news shocks. We conduct a battery of checks to establish the robustness of our findings.

Overall, our findings have two important implications for research on news driven business cycles. First, they provide strong support for shifting focus to IST news shocks when investigating the role of news (or foresight) in driving business cycles. Second, the findings are in sharp contrast to those obtained in estimated DSGE models with IST news shocks (Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012)). In these models, IST news shocks turn out to have little quantitative relevance in terms of accounting for the variance shares of output, consumption, investment, and hours. Moreover, beyond very specific calibrations of the underlying parameters, IST news shocks typically do not produce comovement, and especially so in estimated DSGE models. This apparent disconnect between empirically identified effects of IST news shocks using the VAR methodology and those from estimated DSGE models suggests that an important avenue for further research is to consider structural mechanisms that can enhance the role of IST news shocks in estimated dynamic general equilibrium models.

The remainder of the paper is organized as follows. Section 2 describes the econometric strategy. Section 3 provides information on data used and presents the main empirical evidence. Section 4 summarizes key sensitivity analyses and robustness checks. Section 5 provides implications of our findings for DSGE models. Finally, section 6 concludes.

2 Econometric Strategy

We assume that investment-specific technological progress follows a stochastic process driven by two shocks. First, an unanticipated shock which impacts the level of IST in the same period in which agents observe it. We refer to this as the unanticipated IST shock. This shock was introduced in the pioneering work of Greenwood et al. (1988) and empirically identified using long-run restrictions in Fisher (2006). Second, a shock which the agents observe in advance but it impacts the level of IST in the future. We refer to this as the IST news shock.

2.1 Identifying IST news shocks

We consider a VAR that includes empirical measures of IST, TFP, and several macroeconomic aggregates. The IST news shock is identified as the shock that best explains future movements in IST over a horizon of fifteen years and that is orthogonal to both current TFP and current IST. This identification approach requires finding the linear combination of VAR innovations contemporaneously uncorrelated with current TFP and IST which maximally contributes to IST's future forecast error variance. The restriction with respect to IST is important for identification as it imposes on the identified shock to have no contemporaneous effect on IST, which complies with the definition of a news shock.

As noted in the introduction, a potential concern in identifying IST news shocks is that the inverse of the real price of investment may not equal true IST. We, therefore, carefully account for the possibility of a wedge between the two in section 4 and show that our findings are robust.

Formally, our identification strategy is an extension of the Barsky and Sims (2011)'s maximum forecast error variance (MFEV) approach which they employ to identify TFP news shocks.[3] We

[3]See Faust (1998), Uhlig (2003), and Uhlig (2004) for early work on the MFEV identification approach. There are several reasons why the MFEV identification is more advantageous than using long-run restrictions,

add two additional restrictions described above to the method proposed by Barsky and Sims (2011) to identify IST news shocks. Let y_t be a kx1 vector of observables of length T. Let the reduced form moving average representation in the levels of the observables be given as

$$y_t = B(L)u_t \tag{1}$$

where $B(L)$ is a kxk matrix polynomial in the lag operator, L, of moving average coefficients and u_t is the kx1 vector of reduced-form innovations. We assume that there exists a linear mapping between the reduced-form innovations and structural shocks, ε_t, given as

$$u_t = A\varepsilon_t \tag{2}$$

Equation (1) and (2) imply a structural moving average representation

$$y_t = C(L)\varepsilon_t \tag{3}$$

where $C(L) = B(L)A$ and $\varepsilon_t = A^{-1}u_t$. The impact matrix A must satisfy $AA' = \Sigma$, where Σ is the variance-covariance matrix of reduced-form innovations. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, $\widetilde{A}$ (we choose the convenient Choleski decomposition), the entire space of permissible impact matrices can be written as $\widetilde{A}D$, where D is a k x k orthonormal matrix ($D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).

The h step ahead forecast error is

$$y_{t+h} - E_t y_{t+h} = \sum_{\tau=0}^{h} B_\tau \widetilde{A} D \varepsilon_{t+h-\tau} \tag{4}$$

where B_τ is the matrix of moving average coefficients at horizon τ. The contribution to the forecast

as used in Beaudry and Portier (2006) and Beaudry and Lucke (2010) to identify TFP news shocks using a vector-error-correction model (VECM). Identification using long-run restrictions may suffer from small sample biases (Faust and Leeper (1997)). In fact, Francis et al. (2012) find that the MFEV approach is superior in finite samples than using long-run restrictions. Another difficulty with using long-run restrictions is that they require precise assumptions about the stochastic trend in the variable of interest (which can be a subject of debate) or the number of common stochastic trends among the variables of interest in a vector-error correction model. Fisher (2010) discusses how the latter assumption can affect inference on the importance of TFP news shocks. Under the MFEV approach, estimating the VAR system in levels will give consistent estimates of the impulse responses.

error variance of variable i attributable to structural shock j at horizon h is then given as

$$\Omega_{i,j} = \sum_{\tau=0}^{h} B_{i,\tau}\widetilde{A}\gamma\gamma'\widetilde{A}'B'_{i,\tau} \tag{5}$$

where γ is the jth column of D, $\widetilde{A}\gamma$ is a kx1 vector corresponding with the jth column of a possible orthogonalization, and $B_{i,\tau}$ represents the ith row of the matrix of moving average coefficients at horizon τ. We put TFP and IST in the first and second positions in the system, respectively, and index the unanticipated TFP and IST shocks as 1 and 2, respectively. Finally, the news shock is indexed as 3. The IST news shocks identification requires finding the γ which maximizes the sum of contribution to the forecast error variance of IST over a range of horizons, from 0 to H (the truncation horizon), subject to the restriction that these shocks have no contemporaneous effect on TFP and IST. Formally, this identification strategy requires solving the following optimization problem

$$\begin{aligned}
\underset{\gamma}{\text{argmax}} \sum_{h=0}^{H} \Omega_{2,3}(h) &= \underset{\gamma}{\text{argmax}} \sum_{h=0}^{H}\sum_{\tau=0}^{h} B_{2,\tau}\widetilde{A}\gamma\gamma'\widetilde{A}'B'_{2,\tau} && (6)\\
\text{subject to } \widetilde{A}(1,j) &= 0 \;\; \forall j > 1 && (7)\\
\widetilde{A}(2,j) &= 0 \;\; \forall j > 2 && (8)\\
\gamma(1,1) &= 0 && (9)\\
\gamma(2,1) &= 0 && (10)\\
\gamma'\gamma &= 1 && (11)
\end{aligned}$$

The first four constraints impose on the identified news shock to have no contemporaneous effect on TFP and IST. The fifth restriction that imposes on γ to have unit length ensures that γ is a column vector belonging to an orthonormal matrix. This normalization implies that the identified shocks have unit variance.

We also consider an alternative identification strategy that estimates the joint contribution of TFP and IST news shocks.[4] Let the TFP news shock be defined as the fourth element of ε_t. Let δ be the fourth column of D. Then, the joint estimation of γ and δ requires solution to the following constrained maximization problem:

[4] We thank an anonymous referee for this suggestion.

$$
\begin{aligned}
\underset{\gamma,\delta}{\operatorname{argmax}} \left(\sum_{h=0}^{H} \Omega_{2,3}(h) + \sum_{h=0}^{H} \Omega_{1,4}(h) \right) &= \underset{\gamma,\delta}{\operatorname{argmax}} \sum_{h=0}^{H} \sum_{\tau=0}^{h} \left[B_{2,\tau} \tilde{A} \gamma \gamma' B_{2,\tau}' + B_{1,\tau} \tilde{A} \delta \delta' B_{1,\tau}' \right] && (12) \\
\text{subject to } \tilde{A}(1,j) &= 0 \ \ \forall j > 1 && (13) \\
\tilde{A}(2,j) &= 0 \ \ \forall j > 2 && (14) \\
\gamma(1) &= 0 && (15) \\
\gamma(2) &= 0 && (16) \\
\delta(1) &= 0 && (17) \\
\delta(2) &= 0 && (18) \\
\gamma'\gamma &= 1 && (19) \\
\delta'\delta &= 1 && (20) \\
\gamma'\delta &= 0 && (21)
\end{aligned}
$$

We implement the joint estimation of γ and δ by solving the constrained maximization problem in 12-21. Since this problem can no longer be reduced to an eigenvalue-eigenvector problem as in Uhlig (2004) and Barsky and Sims (2011), we resort to using a numerical optimization procedure where ten million draws of orthogonal pairs of vectors are randomly drawn from which the couple that maximize the objective function (12) are picked. The specific steps are as follows: First, randomly draw a kx2 matrix P of NID(0,1) random variables. Derive the QR decomposition of P such that $P = QR$ and $QQ' = I$ and let $D = Q$.[5] Second, without loss of generality, we let the first column of D correspond to the IST news shock (i.e., γ) and the second column represent the TFP news shock (i.e., δ); we add two zeroes to both γ and δ and use the resulting vectors to compute the value of the objective function.[6] Third, we repeat steps 1 and 2 10^7 times. Fourth, we pick the maximal value obtained from step 2; the matrix D that corresponds to this maximal value contains the pair of identified columns from which we compute the impulse responses and forecast error variance shares.

[5]As discussed by Rubio-Ramirez et al. (2010), this constitutes an efficient method for generating orthonormal matrices.

[6]The addition of the two zeroes ensures that the identified news shocks are contemporaneously orthogonal to both TFP and IST.

3 Empirical Evidence

3.1 Data

The inverse of the real price of investment serves as the measure of IST that we use in the empirical analysis.[7] The real price of investment is the ratio of the investment deflator, P_t^I and the consumption deflator, P_t^C. That is, the measure of IST is

$$IST_t = \left(\frac{P_t^I}{P_t^C} \right)^{-1} \tag{22}$$

The consumption deflator corresponds to nondurable and service consumption obtained from the National Income and Product Account (NIPA). For the investment deflator we consider two different price deflators. First, a NIPA price deflator which corresponds to equipment and software investment and durable consumption. One concern noted in the literature is that incomplete quality adjustments in the NIPA investment price deflator may underestimate measured IST progress. Hence, Greenwood et al. (1997), Greenwood et al. (2000), and Fisher (2006), used the Gordon (1990) quality-adjusted price series for new equipment, extended by Cummins and Violante (2002). Our second choice of deflator is this updated GCV deflator which we use as robustness check in the next section. The NIPA deflator allows us to have a bigger sample size and, as stressed by Justiniano et al. (2011), it includes quality adjustments that generate price declines in accordance with other studies based on micro data (Landefeld and Grimm (2000)). We, therefore, use it for our benchmark results.

The data covers the period from 1951:Q1 to 2012:Q1. For the TFP series, we 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).[8] 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 (as in Justiniano

[7] IST technical change makes new equipment either less expensive or better than the old equipment. The latter is also referred to as capital embodied technical change. Following Greenwood et al. (1997), we use the broader term, namely, investment-specific technology.

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

et al. (2010)). The nominal series are converted to per capita terms by dividing by the civilian non-institutionalized population aged sixteen and over. We use the corresponding chain-weighted deflators to obtain the real series and denote them as GDP_t, C_t, and I_t, respectively. The hours series is log of total hours worked in the non-farm business sector, denoted as N_t. Inflation, π_t, is measured as the percentage change in the CPI for all urban consumers, and interest rate, i_t, is the three month Treasury Bill rate.[9] Credit spread (risk premium), cs_t, is measured as 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).

In the benchmark VAR , y_t is an 9x1 vector of variables given as

$$y_t' = [\log(TFP_t)\ \log(IST_t)\ i_t\ \pi_t\ \log(GDP_t)\ \log(I_t)\ \log(C_t)\ \log(N_t)\ cs_t] \tag{23}$$

and the system is estimated in levels. As noted earlier, the levels specification will yield consistent estimates of the impulse responses. The Akaike criteria favors three lags, the Hannan-Quinn information and Schwartz criteria favor two lags, while the likelihood ratio test statistic chooses seven lags. Given the large number of variables in the VAR, a middle ground of four lags is chosen. We choose $H = 60$ as a benchmark truncation horizon. This fifteen year horizon is sufficiently long to account for potential long run effects of IST news shocks on IST.[10]

3.2 Impulse responses and comovement

Figure 1 shows the estimated impulse responses of all the variables to a positive one standard deviation IST news shock from the benchmark VAR, with the dashed lines representing 1st and 99th percentile confidence bands. These bands are constructed from a residual based bootstrap procedure repeated 2000 times. We use the Hall confidence interval (see Hall (1992)) which attains the nominal confidence content, at least asymptotically, under general conditions and has relatively good small sample properties as shown by Kilian (1999). Following a positive IST news shock, IST does not change on impact, by construction, after which it grows gradually rising by 0.75% after five years (20 quarters) and peaks after 30 years at 1.68% higher than its pre-shock value

[9]To convert monthly population, inflation, and interest rate series to quarterly series, we use the last monthly observation from each quarter.

[10]We consider robustness to alternative lag lengths and different truncation horizons in section 4.

(not shown in the figure). Output, investment, consumption, and hours all jump up on impact, with the responses being both statistically and economically significant at 0.28%, 0.27%, and 0.22% for output, consumption, and hours, respectively, and 0.85% for investment. Output, investment, and hours reach their peak after six quarters while consumption peaks after forty quarters. The significant positive conditional comovement among aggregate variables on impact is compatible with IST news shocks being an important source of fluctuations. Moreover, the identified IST news shock series significantly raises the three month T-Bill rate with a lag of one period while it significantly reduces inflation on impact. The effect on TFP is insignificant.

Table 1 presents estimates of both unconditional and conditional correlations between the growth rate of output and the growth rates of consumption, investment, and hours. The conditional correlations estimates are based on the benchmark VAR model where the conditioning is made with respect to IST news shocks.[11] These estimates can be used to infer the capability of IST news shocks to generate business cycles. The first column of Table 1 shows the unconditional correlations computed directly from the data. These are high, as expected, reflecting the well known comovement property of the business cycle, that output, consumption, investment, and hours move in tandem. The second column of Table 1 shows the correlations of output with consumption, investment, and hours, conditional on the IST news shock. These are very high at 0.90, 0.96, and 0.93, respectively, and are all statistically significant at the 1% level. The large and positive conditional correlations are an indication that IST news shocks are capable of generating business cycles.

3.3 Forecast error variance decompositions

Figure 2 shows the share of the forecast error variance of the variables in the VAR attributable to IST news shocks, and unanticipated IST and TFP shocks over a range of five years. IST news shocks account for 41% of the forecast error variance share of IST at the five years horizon, and 67% at the ten year horizon (not shown). The IST news shock and the unanticipated IST innovation combine to account for over 93% of the forecast error variance of IST at frequencies up to ten years. At the five year horizon, 95% of IST fluctuations are explained by the two shocks. That such a

[11] The conditional correlations are computed as in Galí (1999).

small portion of IST remains unexplained at both short and long horizons validates the assumption underlying identification that most of the movements in IST can be attributed to only two shocks, and suggests that the identification method has done a good job at identifying the IST news shock.

IST news shocks account for a large share of the forecast error variance of macroeconomic aggregates at business cycle frequencies. In particular, they account for 61% of output fluctuations at the one year horizon and 73% at the two year horizon. IST news shocks account for 73% of consumption and 71% of hours forecast error variance at the two year horizon, respectively, and 60% of investment forecast error variance. The large variance shares show that IST news shocks are a substantial source of the U.S. business cycle fluctuations.

3.4 Joint estimation results

Figures 4 and 5 show the impulse responses and the forecast error variance shares, respectively, based on the alternative identification strategy described in section 2.1 that estimates the joint contribution of TFP and IST news shocks. There are two important points to note. First, the IST news shock generates strong co-movement whereas the TFP news shock does not. Second, the contribution of IST news shocks to aggregate fluctuations substantially dominates that of TFP news shocks. The findings from this joint estimation provide a strong reinforcement of the results from the benchmark estimation.

3.5 Accounting for U.S. recessions

Figure 3 shows the time series of identified IST news shocks from the benchmark VAR. The shaded areas represent recession dates as defined by the National Bureau of Economic Research (NBER). To make the figure more readable, we show the one year moving average of the identified shock series as opposed to the actual series. Negative IST news shocks are associated with nine of the last ten U.S recessions, the exception being the 1981-1982 recession. Furthermore, a series of positive IST news shocks is prevalent in the mid to late 1990's confirming the view that the ten year long 1990's expansion was in part induced by positive news about future IST. The story that emerges from Figure 3 is consistent with the results from the historical decomposition discussed below which indicate that IST news shocks were an important driver of U.S business cycles in the last sixty years. Table 2 shows the historical contribution of IST news shocks to the ten NBER determined U.S. recessions since 1951. In particular, for each recession the contribution of IST news to the percentage change in output per capita from peak to trough (in deviation from trend growth) is calculated. We assume a 1.7% output per capita steady state annual growth, which is consistent with the average growth rate of output per capita over the sample. The results indicate that IST news were a driving force behind nine of the last ten U.S recessions. The only recession to which IST news did not contribute was the 1981-1982 recession. The most recent recession (2007-2009), in which output loss was 8.8%, seems to have been driven in part by IST news shocks which contributed 4.1% to that accumulated decline. IST news shocks also contributed 1.3% and 5.2% to the accumulated 2.6% and 7.8% output per capita loss during the 1990-1991 and 1973-1975 recessions, respectively. Moreover, that 0.3% of the 1.5% output loss in the 2001 recession is attributed to IST news shocks is consistent with the view that a downward revision of expectations about future IST took place after the IST news driven boom of the mid to late 1990's. Overall, the historical decomposition results reinforce our main finding that IST news shocks are quantitatively the most important drivers of the U.S. business cycles.

4 Robustness

We conducted extensive sensitivity analyses to establish the robustness of our findings in section 3. We briefly summarize four of these checks here.[12] First, Leeper et al. (2012) have pointed out that the presence of news (foresight) about future fundamentals on part of private agents in the economy can pose an invertibility problem for an econometrician drawing inference based on identified VARs. That is, the identified news shocks from the VAR may not correspond to the news shocks faced by the private agents. From a practical standpoint, one solution 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, we add measures of stock prices (Beaudry and Portier (2006)) and consumer confidence (Barsky and Sims (2011)) to the benchmark VAR as it

[12] We conducted over a dozen robustness checks which are all available in an online appendix at: http://http-server.carleton.ca/ hashkhan/Research/.

is reasonable to assume that these forward-looking variables contain information about future IST progress. The results from this VAR with forward-looking variables are similar to the benchmark findings, indicating that they are robust to the invertibility problem.

Second, as noted above, the benchmark measure of IST is the inverse of the real price of investment. This equality holds in a one sector macroeconomic model, or equivalently, in a two sector model with perfect competition, perfect factor mobility, and identical sectoral production functions (see, for example, Greenwood et al. (2000), Fisher (2006)). However, the presence of imperfect competition and/or imperfect factor mobility can create a wedge that influences the real price of investment, independently of the IST shocks (Ramey (1996), Justiniano et al. (2011)). Using sectoral data, we correct for the effects of the wedge on real price of investment and construct an IST measure adjusted for markups and sectoral factor reallocations. We show that the findings are robust when IST news shocks are identified using this adjusted measure. Furthermore, we provide evidence that the cross-correlations of IST news shocks with other types of shocks such as monetary policy shocks (Romer and Romer (2004)), tax shocks (Romer and Romer (2010)), government spending shocks (Ramey (2011)), and excess bond premium shocks (Gilchrist and Zakrajsek (2012)) are all small and statistically insignificant. Thus what we identify as IST news shocks are not related to these other disturbances.

Third, a recent literature has analyzed the effects of uncertainty shocks in driving U.S. recessions (see, for example, Bloom (2009), Bloom et al. (2012), among others). To distinguish IST news shocks from uncertainty shocks, we include the uncertainty measure based on stock market volatility proposed in Bloom (2009) in the VAR specification, and impose that the identified news shocks are orthogonal to the uncertainty innovation. The variance decompositions relative to the benchmark remain robust.

Fourth, a concern might be about the trends in the data as the VAR is estimated in levels. To address this, we included a time trend in the estimation. The impulse responses from this robustness exercise are similar to the baseline ones, both qualitatively and quantitatively, reflecting forecast error variance shares at business cycle frequencies that are only slightly smaller than the baseline case (now explaining 53%, 50%, 54%, and 47% of the two-year variation in output, hours, investment, and consumption, respectively).

5 Implications for DSGE models with IST news shocks

Our main findings that IST news shocks generate comovement among macroeconomic aggregates and are a major source of U.S. business cycle sit in sharp contrast to the results from the recent estimated DSGE models which have considered IST news shocks among other types of shocks. First, while Jaimovich and Rebelo (2009) highlighted features that enable both TFP news and IST news shocks to generate comovement within a calibrated neoclassical business cycle model, estimated DSGE models with price and wage stickiness tend not to produce comovement in response to IST news shocks. Figure 11 (panels a and b), highlights the lack of comovement which arises for both stationary and non-stationary 4-quarter-ahead IST news shocks, based on the estimated model in Khan and Tsoukalas (2012). Clearly, the impulse responses from the DSGE model are not consistent with those identified in the data using the VAR-based approach. Second, as shown in Table 4, the contribution of IST news shocks to the forecast error variance of output, consumption, hours, and investment in a flexible price-wage estimated DSGE model is relatively small (Schmitt-Grohé and Uribe (2012)) and in a sticky price-wage estimated DSGE model, essentially zero (Khan and Tsoukalas (2012)).

Our results suggest that an important avenue for further research is to consider structural mechanisms that can enhance the role of IST news shocks in estimated DSGE models. In this regard, our implications differ from those of Barsky and Sims (2011). Their results imply that since the responses to identified TFP news shocks resemble those from a standard real business cycle model without the features considered in, for example, Jaimovich and Rebelo (2009), research aimed at generating comovement after TFP news shocks may be less fruitful. By contrast, our empirical findings pose a challenge for existing DSGE models, and suggest that it is worthwhile to uncover mechanisms that can help generate strong comovement and propagation in estimated DSGE models.

6 Conclusion

This paper identifies shocks to future investment-specific technical change - IST news shocks - as a major force in driving post-WWII U.S. business cycles. We consider the empirical VAR approach based on maximum forecast error variance proposed by Barsky and Sims (2011) to identify IST news shocks. Applying this empirical procedure, we found that IST news shocks induce positive comovement, i.e., raise output, consumption, investment, and hours of work, and explain 70% of the business cycle variation in output, hours, and consumption and 60% of that in investment. The results indicate that IST news shocks have played an important role in 9 of the last 10 U.S. recessions. Moreover, IST news shocks dominate unanticipated IST shocks in accounting for business cycle variation of aggregate variables. We conducted several checks to establish the robustness of our findings.

There are two main implications of the findings in this paper for research on news driven sources of business cycles. First, they provide strong support for shifting focus to IST news shocks when investigating the the role of news (or foresight) in driving business cycles. Second, the findings suggest that an important avenue for further research is to consider structural mechanisms that can enhance the role of IST news shocks in estimated dynamic general equilibrium models.

References

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

Basu, S., Fernald, J. and Kimball, M.: 2006, Are technology improvements contractionary?, *American Economic Review* **96**(5), 1418–1448.

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

Beaudry, P. and Portier, F.: 2006, Stock prices, news, and economic fluctuations, *American Economic Review* **96**(4), 1293–1307.

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

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I. and Terry, S.: 2012, Really uncertain business cycles, *Working Paper 18245*, NBER.

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

Davis, J.: 2007, News and term structure in general equilibrium. Unpublished (Northwestern University manuscript).

Faust, J.: 1998, The robustness of identified VAR conclusions about money, *Carnegie-Rochester Conference Series on Public Policy* **49**(1), 207–244.

Faust, J. and Leeper, E.: 1997, When do long run restrictions give reliable results?, *Journal of Business and Economic Statistics* **15**(3), 345–353.

Fernald, J.: 2007, Trend breaks, long-run restrictions, and contractionary technology improvements, *Journal of Monetary Economics* **54**(8), 2467–85.

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

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

Fisher, J.: 2010, Comment on: Letting different views about business cycle compete, *in* D. Acemoglu, K. Rogoff and M. Woodford (eds), *NBER Macroeconomics Annual*, Vol. 24, University of Chicago Press, pp. 457–474.

Francis, N., Owyang, M. and Roush, J.: 2012, A flexible finite horizon identification of technology shocks, *Review of Economics and Statistics (forthcoming)* .

Francis, N. and Ramey, V.: 2005, Is the technology-driven real business cycle hypothesis dead? shocks and aggregate fluctuations revisited, *Journal of Monetary Economics* **52**(8), 1379–99.

Galí, J.: 1999, Technology, employment and the business cycle: Do technology shocks explain aggregate fluctuations?, *American Economic Review* **89**(1), 249–271.

Gilchrist, S. and Zakrajsek, E.: 2012, Credit spreads and business cycles, *American Economic Review* **102**(4), 1692–1720.

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

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

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

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

Hall, P.: 1992, *The Bootstrap and Edgeworth Expansion*, Springer-Verlag.

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

Justiniano, A., Primiceri, G. and Tambalotti, A.: 2010, Investment shocks and business cycles, *Journal of Monetary Economics* **57**(1), 132–145.

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

Khan, H. and Tsoukalas, J.: 2012, The quantitative importance of news shocks in estimated dsge models, *Journal of Money, Credit and Banking* **44**(8), 1535–1561.

Kilian, L.: 1999, Finite-sample properties of percentile and percentile-t bootstrap confidence intervals for impulse responses, *The Review of Economics and Statistics* **81**(4), 652–660.

Landefeld, S. and Grimm, B.: 2000, A note on the impact of hedonics and computers on real GDP, *Survey of Current Business* .

Leeper, E., Walker, T. and Yang, S.-C. S.: 2012, Foresight and information flows, *Manuscript*, Indiana University.

Papanikolaou, D.: 2011, Investment shocks and asset prices, *Journal of Political Economy* **119**(4), 639–685.

Ramey, V.: 1996, Can technology improvements cause productivity slowdowns?: Comment, *in* B. Bernanke and J. Rotemberg (eds), *NBER Macroeconomics Annual*, Vol. 11, University of Chicago Press, pp. 268–274.

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

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

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

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

Schmitt-Grohé, S. and Uribe, M.: 2012, What's news in business cycle?, *Econometrica* **80**, 2733–2764.

Sims, E.: 2012, News, non-invertibility, and structural VARs, *Advances in Econometrics* **28**, 81–136.

Uhlig, H.: 2003, What moves real GNP?, *Unpublished manuscript.*

Uhlig, H.: 2004, Do technology shocks lead to a fall in total hours worked?, *Journal of European Economic Association* **2**(2/3), 361–371.

Table 1: **Correlations**

	Unconditional	Conditional
Output	1	1
Consumption	0.54	0.90 [0.40, 0.96]
Investment	0.84	0.96 [0.66, 0.99]
Hours	0.73	0.93 [0.64, 0.96]

Notes: Unconditional and conditional correlations between the growth rate of output and the growth rates of consumption, investment, and hours. The unconditional correlations are computed directly from the data whereas the conditional correlations estimates are based upon the benchmark VAR model where it is assumed that IST news shocks are the only shocks hitting the economy. Numbers in square brackets represent the 1st and 99th bootstrapped percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times.

Table 2: **Historical contribution of IST news shocks to output per capita loss in U.S. recessions**

Recession	% change in output per capita	Contribution of IST news shocks
1953:2-1954:2	-5.4	-2.4
1957:3-1958:2	-5.4	-2.2
1960:2-1961:1	-2.8	-1
1969:4-1970:4	-4	-1.5
1973:4-1975:1	-7.8	-5.2
1980:1-1980:3	-3.9	-1.3
1981:3-1982:4	-6.3	1
1990:3-1991:1	-2.6	-1.3
2001:1-2001:4	-1.5	-0.3
2007:4-2009:2	-8.8	-4.1

Notes: The estimates of the contribution of IST news shocks to each of the recessions in our sample period. The first column presents the percentage change from peak to trough of output per capita, relative to trend growth, in every recession. The second column reports the contribution of IST news shocks, based on the benchmark VAR model, to the corresponding output loss. A 1.7% output per capita annual trend growth is assumed, which is consistent with the average growth rate of output per capita over the sample.

Table 3: **Correlations: Identified IST shocks**

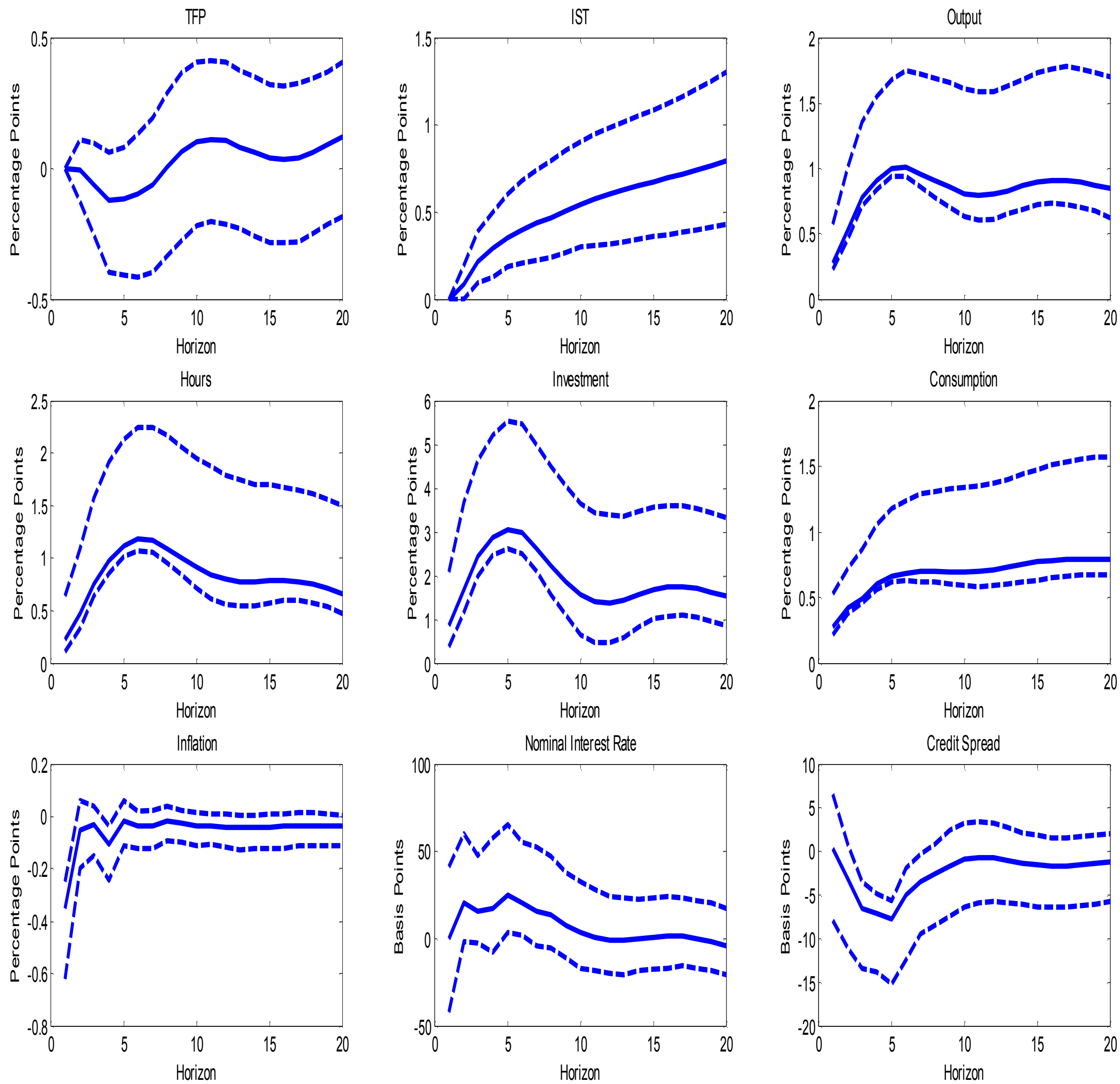
	MFEV approach (This paper)	
	Unanticipated IST	IST news
Unanticipated IST (Fisher (2006)) (using long-run restriction)	0.37	0.78

Table 4: **A comparison of forecast error variance shares of IST news shocks (in %): SVAR versus DSGE.**

	SVAR†	Estimated DSGE models	
	This paper	Schmitt-Grohé and Uribe (2012)*	Khan and Tsoukalas (2012)
		(flexible prices & wages)	(sticky prices & wages)
Output	73	7	0
Consumption	73	1	0
Investment	60	19	0
Hours	71	2	0

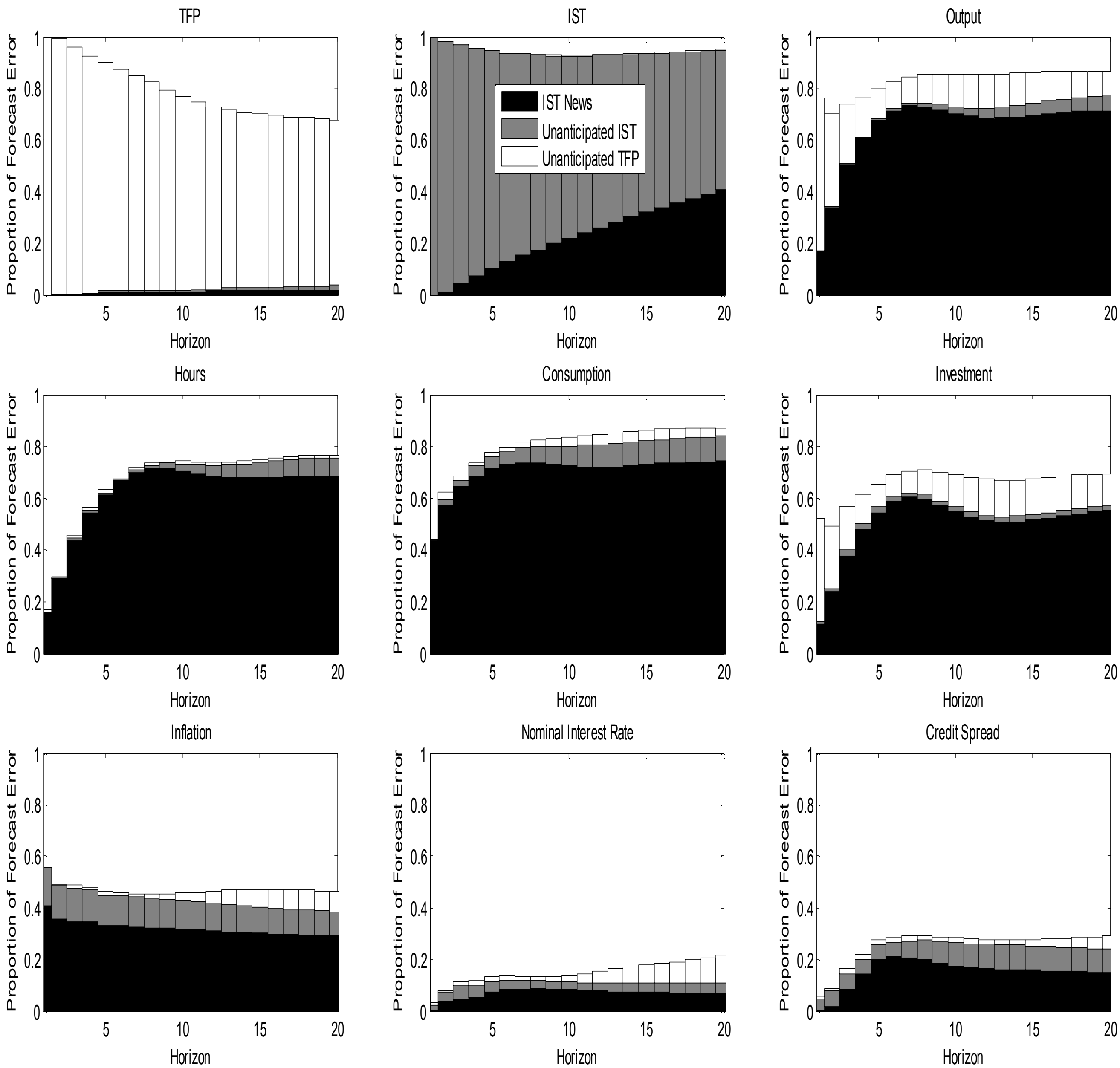
Notes: †Benchmark results for an 8-quarter horizon. *See Table 6 in Schmitt-Grohé and Uribe (2012) and Table 2 in Khan and Tsoukalas (2012).

Figure 1: **Impulse responses to a one standard deviation IST news shock from the benchmark VAR (solid lines).**



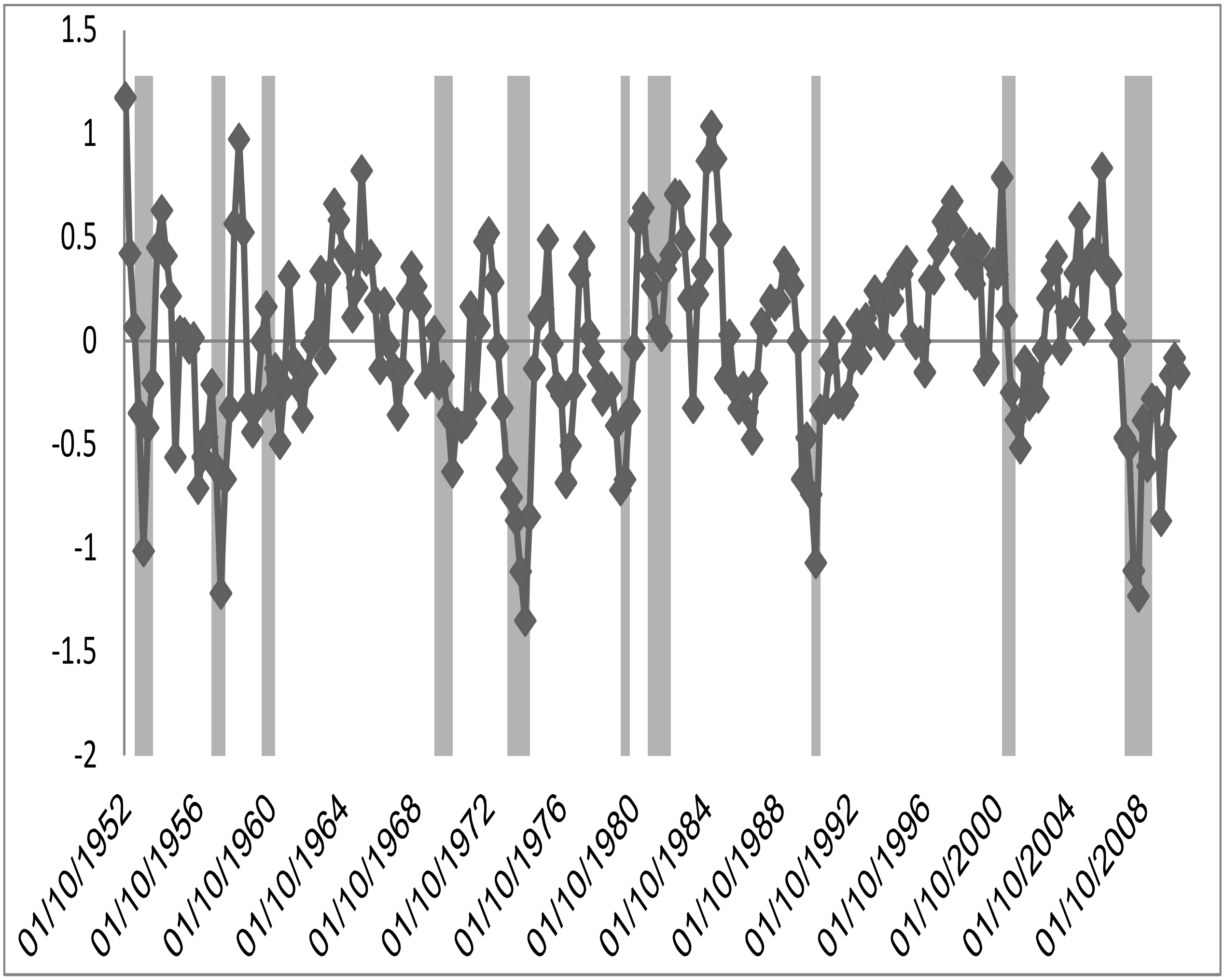
Notes: Dashed lines represent 1st and 99th percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times. Horizon is in quarters.

Figure 2: **The share of forecast error variance attributable to identified shocks (IST News, unanticipated IST and unanticipated TFP) from the benchmark VAR**.



Notes: The sum of relative contributions of all three shocks do not necessarily add up to one as there are potentially additional unidentified shocks also accounting for part of the forecast error variance.

Figure 3: **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 data is smoothed using a one year moving average. Specifically, it is calculated as $\varepsilon_t^s = (\varepsilon_{t-3} + \varepsilon_{t-2} + \varepsilon_{t-1} + \varepsilon_t)/4$. The series begins in 1952:Q4 and ends in 2012:Q1.

Figure 4: **Joint Estimation: Impulse responses to identified IST News shocks and TFP News shocks**.

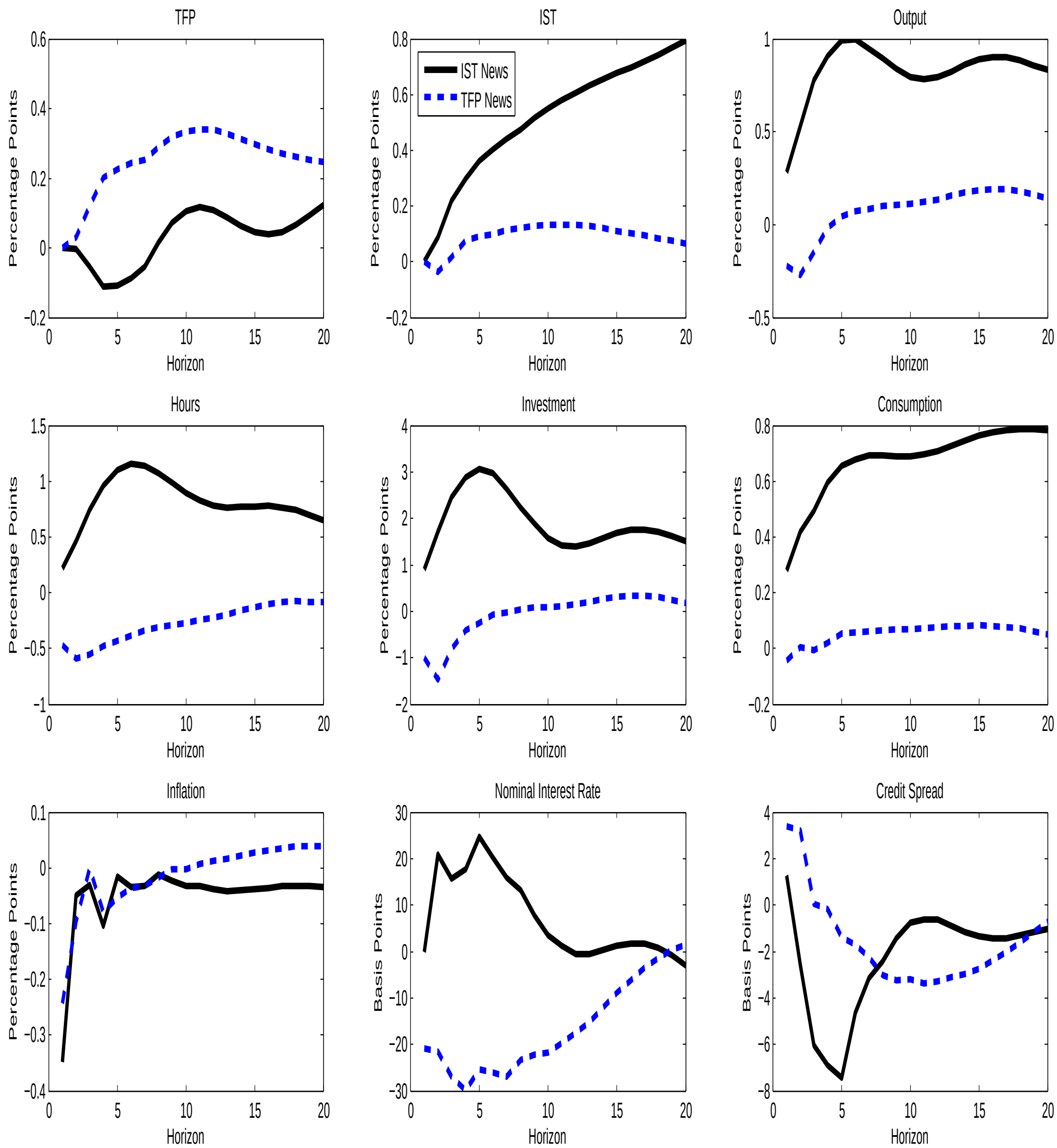


Figure 5: **Joint Estimation: The share of forecast error variance attributable to identified IST News shocks and TFP News shocks**.

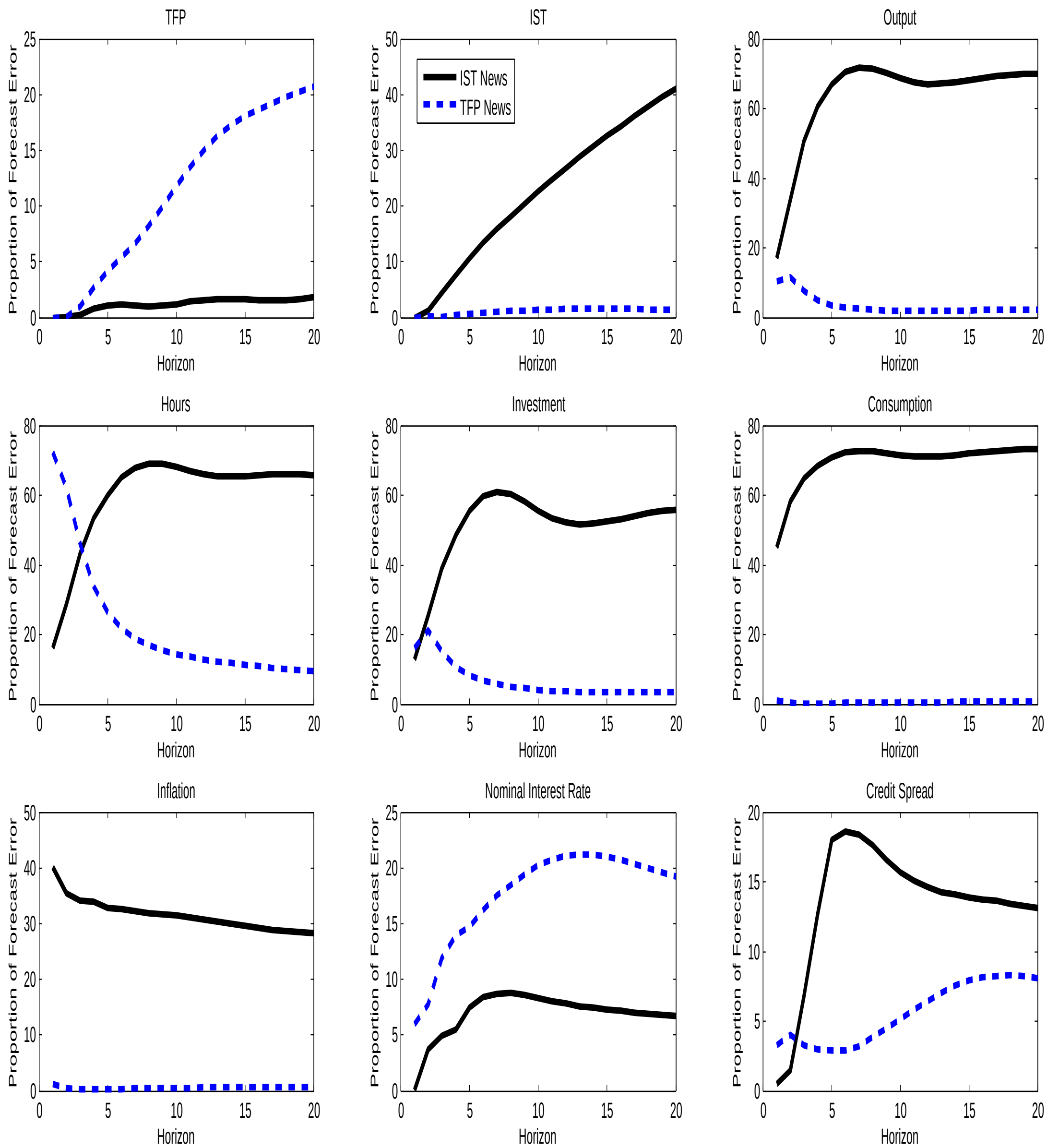
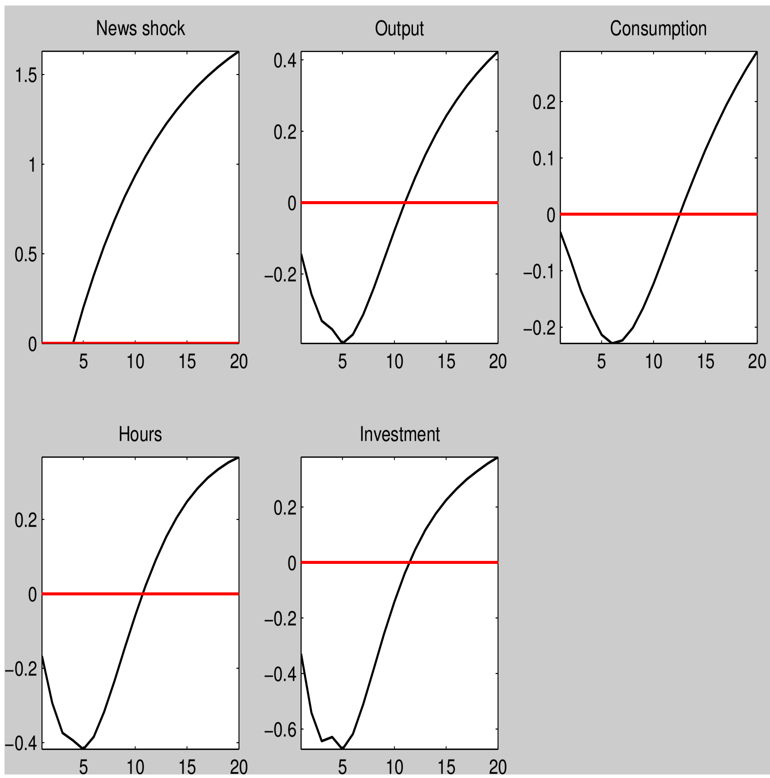
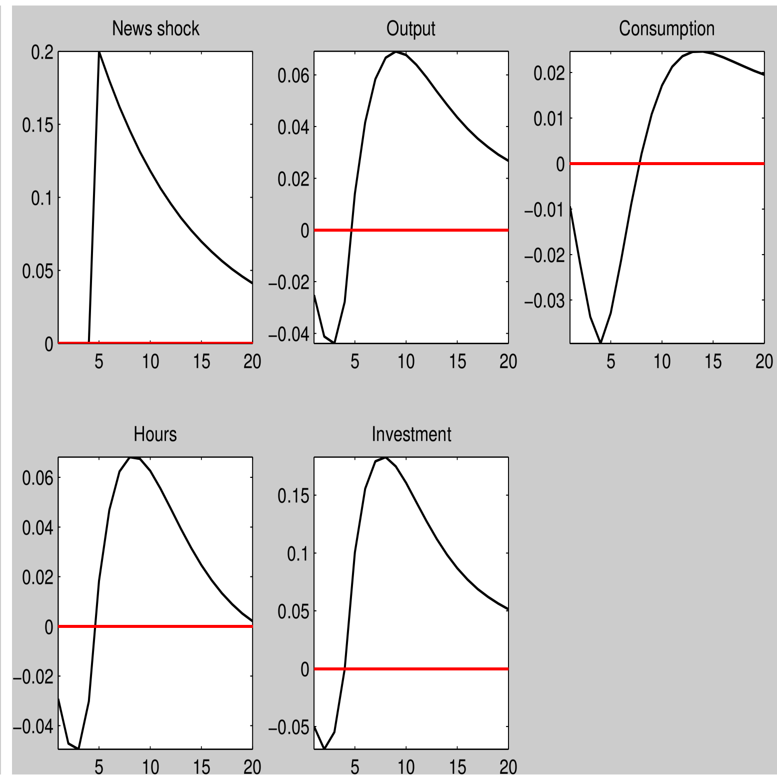


Figure 6: **DSGE model: Impulse responses to IST news shocks**



(a) Non stationary news shock.



(b) Stationary news shock.

Notes: The impulse responses are based on the estimated DSGE model in Khan and Tsoukalas (2012). The IST news horizon is 4 quarters.