Investment-Specific News Dominates TFP News in Driving US Business Cycles

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Abstract

When both Investment-Specific Technology (IST) news and Total Factor Productivity (TFP) news shocks compete, the former substantially dominate the latter in driving post-WWII US business cycles. At the two-year horizon, IST news shocks account for 58 percent of the forecast error variance in output, 56 percent of the variation in hours, 51 percent of investment, and 65 percent of consumption variation. By contrast, TFP news shocks account for less than 10 percent of the variation in output, hours, investment, and consumption. TFP news also fails to produce comovement and statistically significant effects on macroeconomic variables despite using the most recent vintage of TFP data from Fernald (2014). Our findings suggest shifting focus from TFP to IST news when studying news-driven business cycles.

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Key words: Investment-Specific News; TFP News; Shocks; News-Driven Business Cycles

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1 Introduction

Building on the empirical work of Fisher (2006), Beaudry and Portier (2006), and Barsky and Sims (2011), Ben Zeev and Khan (2015) present robust evidence that news about Investment-Specific Technology (IST) is a dominant force behind post-WWII US business cycles. Recently, Sims (2016) and Kurmann and Sims (2016) show that the newer vintage of utilization-adjusted Total Factor Productivity (TFP) data from Fernald (2014) affects inference on TFP news shocks, and produces somewhat more favourable results in terms of the impulse responses of hours and output for this type of news shock relative to those reported in Barsky and Sims (2011). Kurmann and Sims (2016), however, do not consider IST news shocks. In this paper we ask the question: When both IST and TFP news shocks compete, which shock dominates given the most recent 2016 vintage of the the TFP data?

We find that IST news shocks substantially dominate TFP news shocks in driving US business cycles over the 1951Q1-2016Q1 period even when the most recent vintage of the TFP data is used. There are striking differences in the share of forecast error variances accounted for by each of the two types of news shock. At the two-year horizon, IST news shocks account for 58 percent of the forecast error variance in output, 56 percent of the variation in hours, 51 percent of investment, and 65 percent of consumption variation. By contrast, TFP news shocks account for less than 10 percent of the variation in output, hours, investment, and consumption. TFP news shocks also fail to generate comovement with respect to hours, which decrease after a positive TFP news shock.

There are two implications of our findings for the literature on news-driven business cycles that originated with Beaudry and Portier (2006).[1] First, our evidence strongly favours shifting focus from TFP news to IST news. Second, reconciling the strong empirical support for IST news in US data with structural explanations based on estimated Dynamic Stochastic General Equilibrium (DSGE) is a key challenge for future research.

The rest of this paper is organized as follows. Section 2 presents the empirical methodology, identification restrictions, and data. Section 3 presents the results. Section 4 concludes.

[1]See Beaudry and Portier (2014) and Ramey (2016) for a comprehensive review of this literature.

2 Empirical methodology, identification restrictions, and data

Ben Zeev and Khan (2015) extend the Maximum Forecast Error Variance (MFEV) considered in Barsky and Sims (2011) to allow for a joint identification of *both* TFP and IST news shocks. We briefly summarize the empirical methodology and identification restrictions here.

2.1 Empirical methodology and identification of shocks

We assume that both TFP and IST follow a stochastic process driven by two shocks. First, an unanticipated shock which impacts the level of technology in the same period in which agents observe it. We refer to this as the unanticipated shock. Second, a shock which the agents observe in advance but it impacts the level of technology in the future. We refer to this as the news shock. We consider a VAR that includes empirical measures of TFP, IST, and several macroeconomic aggregates. The TFP and IST news shocks are identified as the pair of orthogonal shocks that best explain future movements in TFP and IST over a horizon of fifteen years, respectively, and that are orthogonal to *both* current TFP and current IST. Below we explain in detail how we identify both shocks simultaneously while restricting orthogonality between them.

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

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

where ξ 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.[2] The IST and TFP news shocks are indexed as 3 and 4, respectively. Let γ and δ be the third and fourth columns of D, respectively. Then, the joint estimation of γ and δ requires solution to the following constrained

[2]Effectively, the unanticipated TFP shock is identified as the VAR innovation in TFP, as in Barsky and Sims (2011), while the unanticipated IST shock is identified as the innovation in IST orthogonalized with respect to current TFP.

maximization problem:

$$\begin{aligned}
\underset{\gamma,\delta}{\operatorname{argmax}}\left(\sum_{h=0}^{H}\Omega_{2,3}(h)+\sum_{h=0}^{H}\Omega_{1,4}(h)\right) &= \underset{\gamma,\delta}{\operatorname{argmax}}\sum_{h=0}^{H}\sum_{\tau=0}^{h}\left[B_{2,\tau}\tilde{A}\gamma\gamma' B_{2,\tau}'+B_{1,\tau}\tilde{A}\delta\delta' B_{1,\tau}'\right] && (6)\\
\text{subject to}\ \ \tilde{A}(1,j) &= 0\ \ \forall j>1 && (7)\\
\tilde{A}(2,j) &= 0\ \ \forall j>2 && (8)\\
\gamma(1) &= 0 && (9)\\
\gamma(2) &= 0 && (10)\\
\delta(1) &= 0 && (11)\\
\delta(2) &= 0 && (12)\\
\gamma'\gamma &= 1 && (13)\\
\delta'\delta &= 1 && (14)\\
\gamma'\delta &= 0 && (15)
\end{aligned}$$

We implement the joint estimation of γ and δ by solving the constrained maximization problem in (6)-(15). Since this problem can no longer be reduced to an eigenvalue-eigenvector problem as in Uhlig (2003) and Barsky and Sims (2011), we resort to using a numerical optimization procedure and obtain five million draws of orthogonal pairs of randomly drawn vectors and pick the couple that maximize the objective function (6). The specific steps are as follows: First, we randomly draw a kx2 matrix P of NID(0,1) random variables. We derive the QR decomposition of P such that $P = QR$ and $QQ' = I$, and let $D = Q$.[3] 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.[4] Third, we repeat the first and second steps five million times. Fourth, we pick the maximal value obtained from the second step; 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.

[3]As discussed in Rubio-Ramirez, Waggoner, and Zha (2010), this method constitutes an efficient way for generating orthonormal matrices.

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

We follow the conventional Bayesian approach to estimation and inference by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters. Specifically, we take 1000 draws from the posterior distribution of reduced form VAR parameters, where for each draw we solve optimization problem in (6)-(15); we then use the resulting optimizing γ and δ vectors to compute impulse responses to the identified shocks. This procedure generates 1000 sets of impulse responses which comprise the posterior distribution of impulse responses to our identified shock.

2.2 Data

The real price of investment is the ratio of the investment deflator and the consumption deflator. IST is measured as the inverse of the real price of investment.[5] The consumption deflator corresponds to nondurable and service consumption obtained from the National Income and Product Account (NIPA). For the investment deflator we consider a NIPA price deflator which corresponds to equipment investment and durable consumption. The data covers the period from 1951:Q1 to 2016:Q1.

The main issue that we address in this note is the use of the latest 2016 vintage of Fernald (2014)'s the utilization-adjusted TFP series.[6] The nominal series for output, consumption, and investment, data are taken from the Bureau of Economic Analysis (BEA). Output is measured as GDP, consumption as the sum of non-durables and services, and investment is the sum of personal consumption expenditures on durables and private fixed investment. We convert the nominal series to per capita terms by dividing with 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 the per capita 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; credit spread (risk premium), cs_t, is measured as the spread between the expected return on medium-

[5] Theoretically, sectoral markups and relative input allocations can create a wedge between measured IST and the inverse of the real price of investment. Ben Zeev and Khan (2015) show that the estimated effects of IST news shocks are robust even after accounting for this wedge. This finding indicates that even if the wedge exists, it is not particularly cyclical.

[6] http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/

grade bonds and high-grade bonds (Moody's seasoned Baa corporate bond yield and Aaa corporate bond yield, respectively).[7]

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

$$y_t' = [\log(TFP_t)\ \log(IST_t)\ i_t\ \pi_t\ \log(GDP_t)\ \log(I_t)\ \log(C_t)\ \log(N_t)\ cs_t] \tag{16}$$

and we estimate the system in levels. The levels specification yields consistent estimates of the impulse responses. The Akaike criteria and the Hannan-Quinn information 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 the effects of IST and TFP news shocks on IST and TFP, respectively.

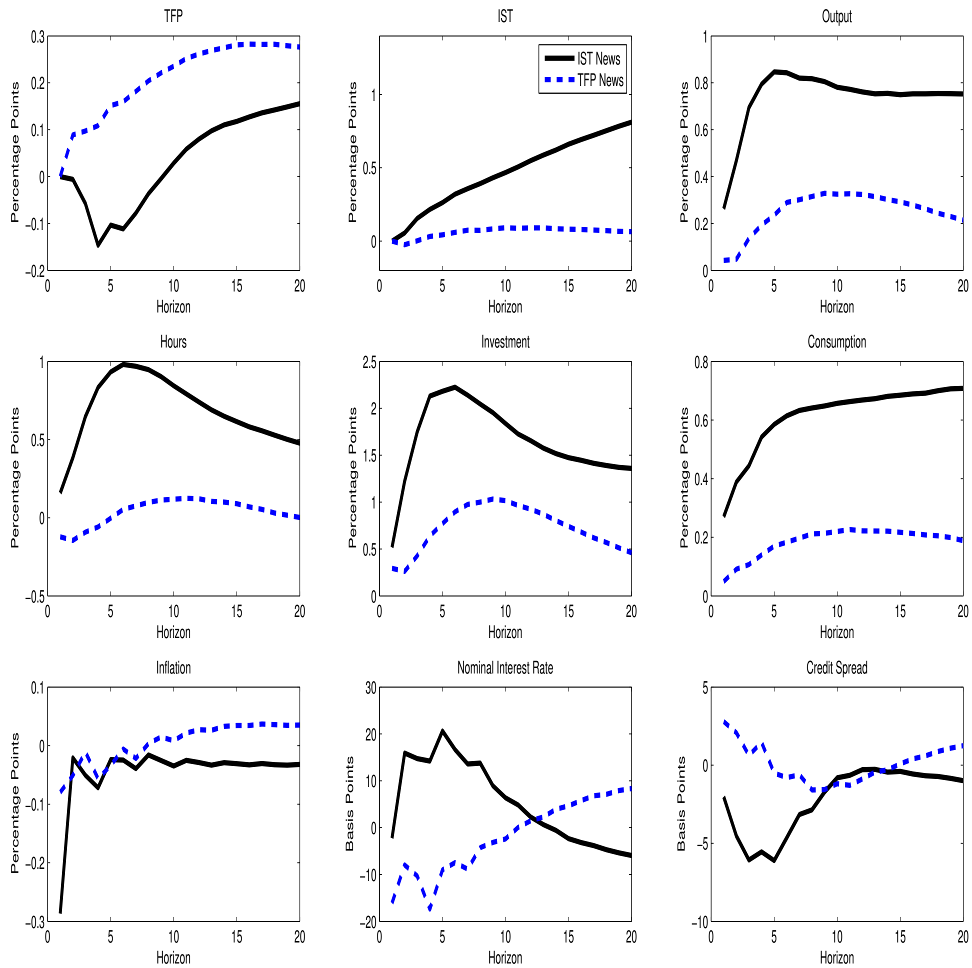
3 Results

3.1 Impulse responses

Figure 1 shows the impulse response functions to a one standard deviation shock to IST news (solid line) and TFP news (dotted line), respectively.

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

Figure 1: **Impulse responses to a one standard deviation IST news (solid line) and TFP news (dotted line) shocks, respectively**



Notes: Horizon is in quarters.

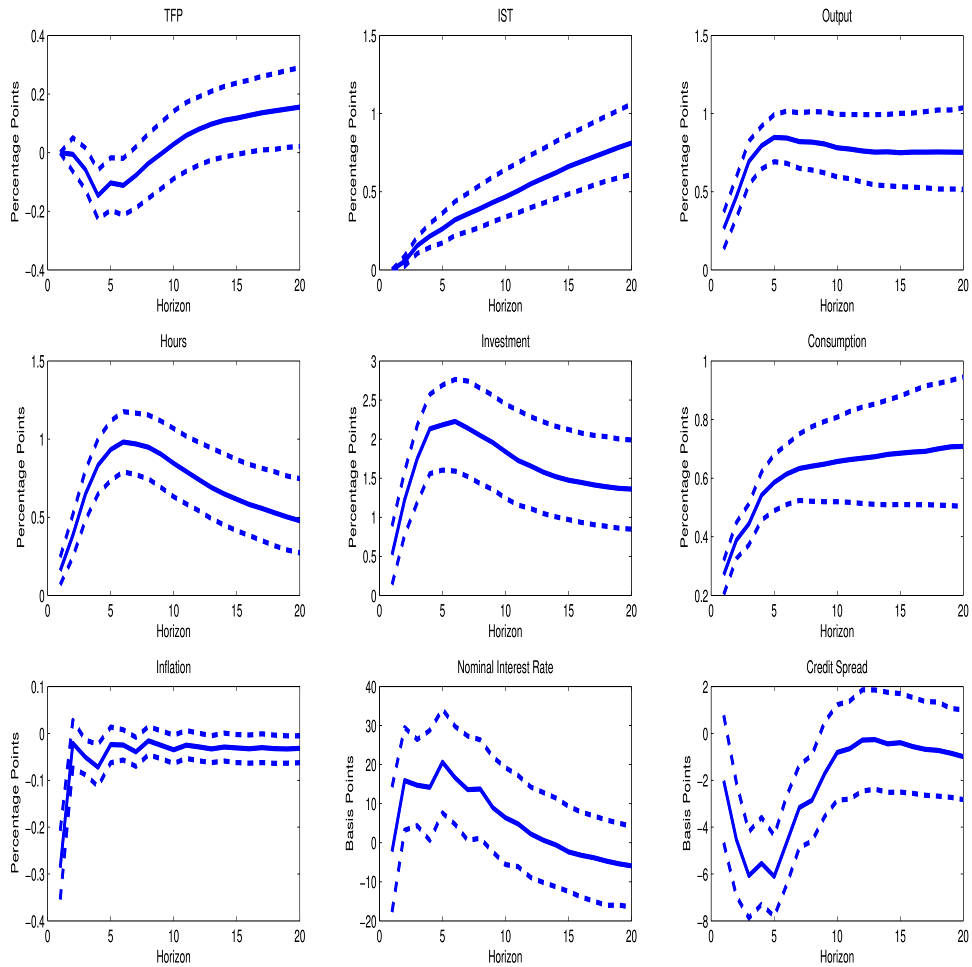
IST news shocks generate strong comovement in key macroeconomic variables—the defining property of business cycles. Output, consumption, hours, and investment all rise after a favourable IST news shocks. Inflation decreases sharply on impact but quickly returns to zero with a muted response thereafter. Nominal interest rate rises and the credit spread decreases, both responses are persistent and hump-shaped.

By contrast, a favourable TFP news shocks generates a small positive response of output, consumption, and investment on impact. Hours, however, decrease after the shock. These impulse responses, therefore, indicate that a TFP news shock does not produce business cycle comovement even when using the most recent 2016 vintage of the utilization-adjusted TFP data.

3.2 Statistical significance

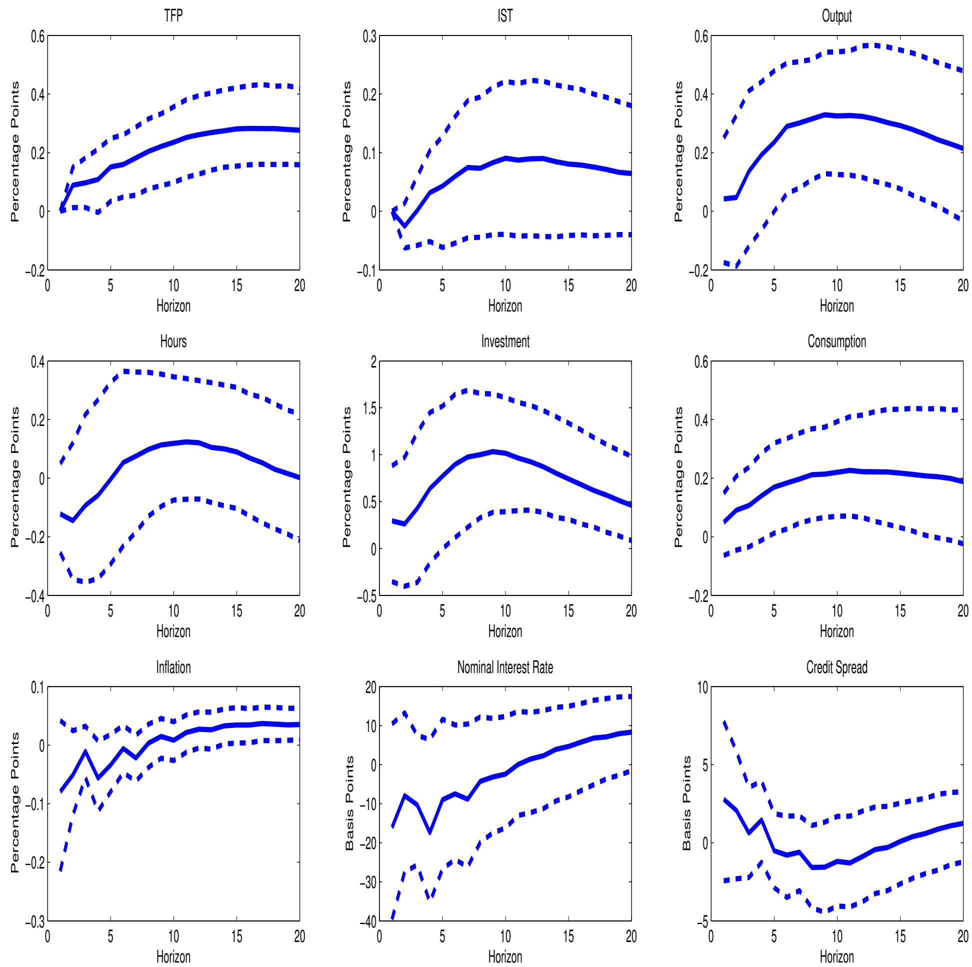
Figure 2 shows the 68% confidence bands associated with the impulse response functions of IST news shocks. The responses of all the major macroeconomic quantities, output, hours, investment, and consumption are statistically significant. On the other hand, all the impact responses to TFP news are statistically insignificant as shown in figure 3, with the confidence bands for all the variables in the VAR including zero impact.

Figure 2: **Impulse responses to a one standard deviation IST news shock**



Notes: Dashed lines represent 68% posterior bands. Horizon is in quarters.

Figure 3: **Impulse responses to a one standard deviation TFP news shock**



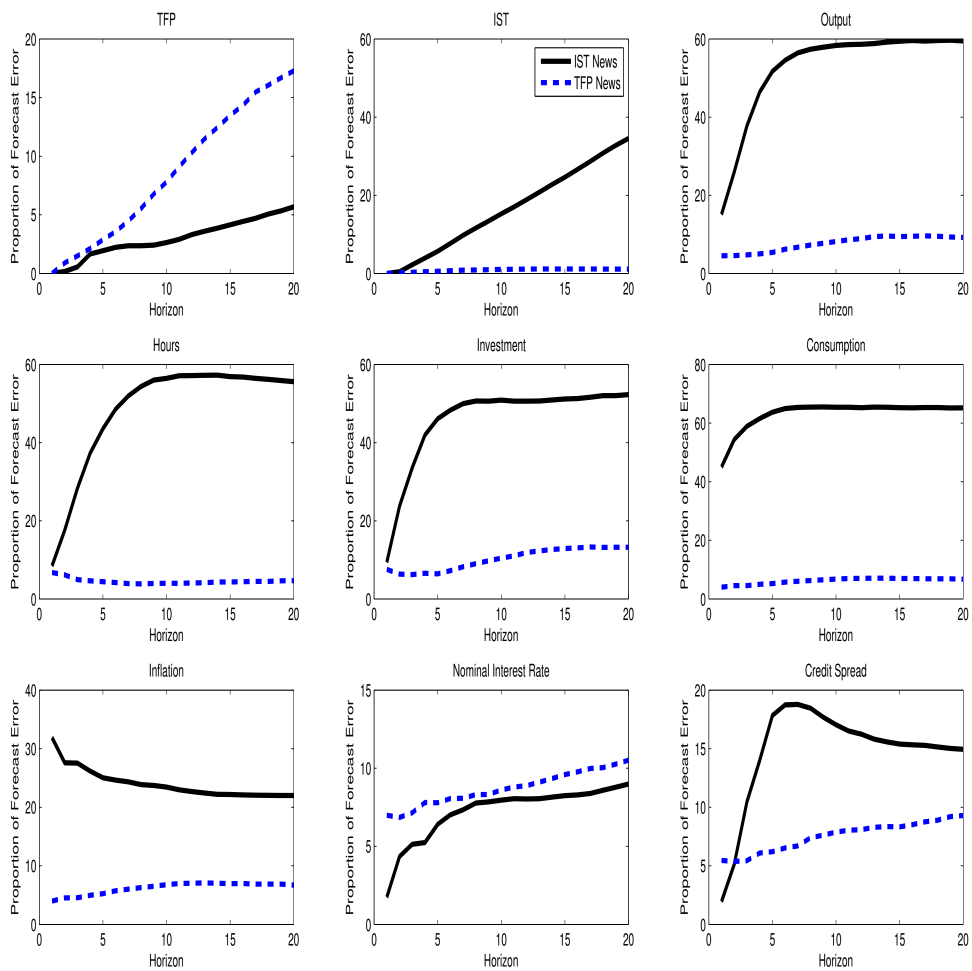
Notes: Dashed lines represent with 68% posterior bands. Horizon is in quarters.

3.3 Variance decompositions

Figure 4 jointly presents the forecast error variance decompositions median estimates for IST and TFP news shocks, respectively, and Figures 5 and 6 depict the respective median estimates along with the 68% posterior bands. There are striking differences in the share of forecast error variances accounted for by each of the two types of news shock. At the two-year horizon, IST news shocks account for 58 percent of the forecast error variance in output, 56 percent variation in hours, and 51 percent of investment, and 65 percent of consumption variation. Turning to inflation and financial variables, these shocks account for 24 percent of the variation in inflation and approximately 8 and 18 percent of the variation in nominal interest rates and the credit spread, respectively.

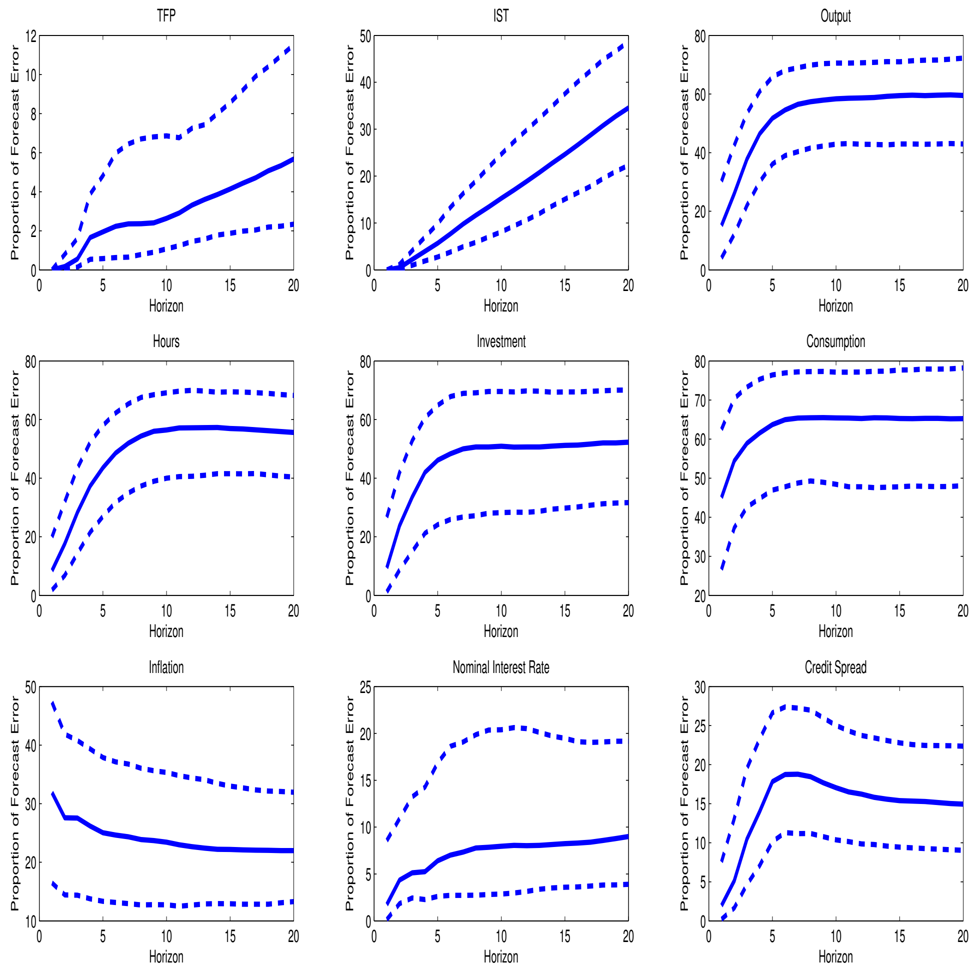
By contrast, the contribution of TFP news shocks to the forecast error variance of key macroeconomic variables is significantly smaller. TFP news shocks account for less than 10 percent of the variation in output, consumption, investment, and hours. These shocks only account for 7 percent of the variation in inflation, and only about 8 percent of the variation in the nominal interest rate and the credit spread.

Figure 4: **Forecast error variance decompositions for IST news (solid line) and TFP news (dotted line) shocks, respectively**.



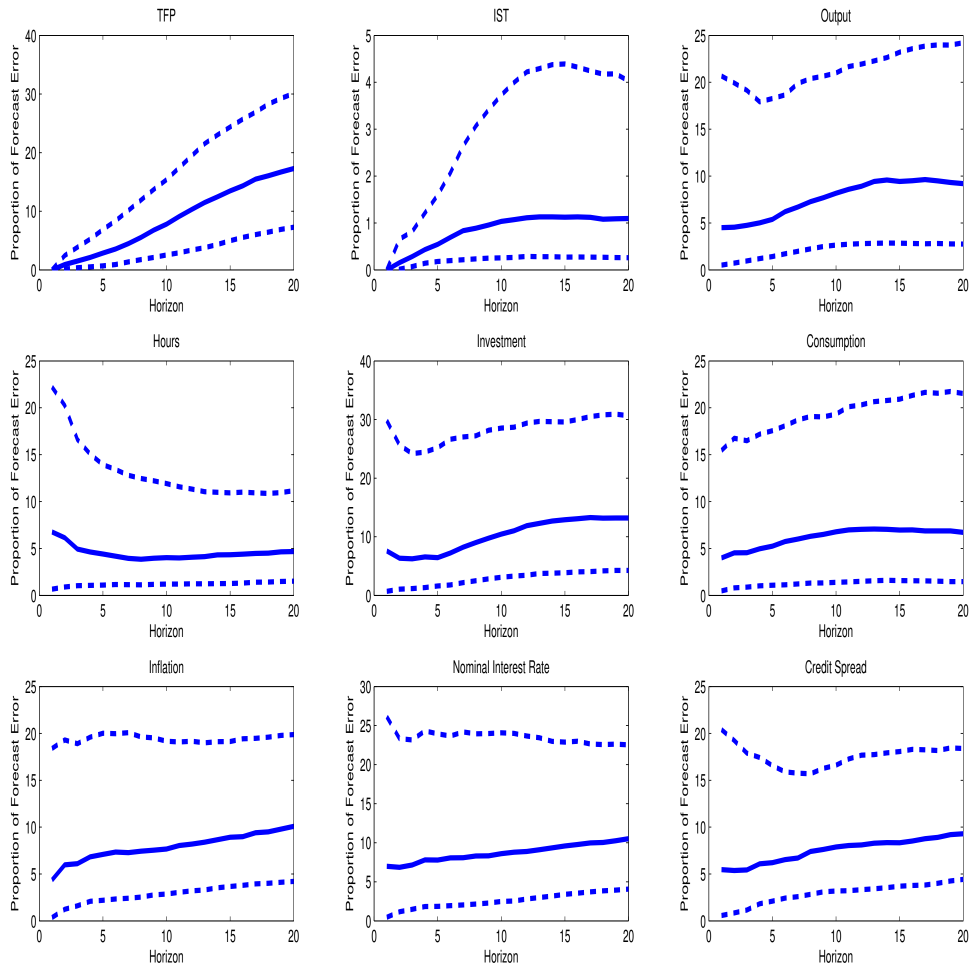
Notes: Horizon is in quarters.

Figure 5: **Forecast error variance decompositions for IST news shocks**.



Notes: Dashed lines represent with 68% posterior bands. Horizon is in quarters.

Figure 6: **Forecast error variance decompositions for TFP news shocks.**



Notes: Dashed lines represent with 68% posterior bands. Horizon is in quarters.

4 Conclusion

We let IST news shocks compete with TFP news shocks and present evidence that the former substantially dominate the latter in driving post-WWII US business cycles. A key aspect of our findings is that we use the most recent 2016 vintage of Fernald (2014)'s utilization-adjusted TFP data. This is important because when TFP news shocks alone are identified the newer vintage produces somewhat more favourable results for this shock as shown in Sims (2016) and Kurmann and Sims (2016). We show that IST news shocks produce positive business cycle comovement of consumption, investment, and hours with output whereas TFP news shocks do not. The estimated impact effects of TFP news shocks on macroeconomic aggregates are all statistically insignificant, whereas for IST news shocks they are all significant. Our findings suggest shifting focus from TFP news to IST news, and towards reconciling the empirical evidence with structural explanations based on estimated DSGE models.

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