American Economic Journal: Macroeconomics 2022, 14(4): 210–243
https://doi.org/10.1257/mac.20170066

News Shocks under Financial Frictions†

By Christoph Görtz, John D. Tsoukalas, and Francesco Zanetti*

We examine the dynamic effects of TFP news shocks in the context of frictions in financial markets. We document two new facts. First, a shock to future TFP generates a significant decline in credit spread indicators along with a robust improvement in credit supply indicators. Second, we establish a tight link between TFP news shocks and shocks that explain the majority of un-forecastable movements in credit spread indicators. A DSGE model enriched with a financial sector of the Gertler-Kiyotaki-Karadi type generates very similar quantitative dynamics. (*JEL* E12, E31, E32, E44, G12, G21)

The news-driven business cycle hypothesis formalized in Beaudry and Portier (2004) and restated in Jaimovich and Rebelo (2009) posits that changes in expectations of future fundamentals are an important source of business cycle fluctuations. Movements in financial markets encapsulate changes in expectations about the future and are a powerful mechanism that triggers changes in economic activity. A vast body of research finds that financial markets are characterized by frictions that lead to credit spreads—differences in yields between private debt instruments and government bonds of comparable maturities—whose movements contain important information on the evolution of the real economy and encompass predictive content for future economic activity.[1]

In this paper we quantify the empirical significance and dynamic effects of total factor productivity (TFP) news shocks in light of propagation through financial frictions. We investigate the issue using two widely used methods (VAR and DSGE)

* Görtz: University of Birmingham, Department of Economics (email: c.g.gortz@bham.ac.uk); Tsoukalas: University of Glasgow, Adam Smith Business School/Economics (email: john.tsoukalas@glasgow.ac.uk); Zanetti: University of Oxford, Department of Economics (email: francesco.zanetti@economics.ox.ac.uk). Simon Gilchrist was coeditor for this article. We thank four anonymous referees, Jesús Fernández-Villaverde, James Hamilton, Alejandro Justiniano, Lilia Karnizova, Hashmat Khan, Thomas Lubik, Charles Nolan, Giorgio Primiceri, Plutarchos Sakellaris, Frank Schorfheide, Felipe Schwarzman, Stephanie Schmitt-Grohé, Albert Queralto, Harald Uhlig, Mark Watson, Tony Yates, Steffen Ahrens and Nadav Ben Zeev for extremely helpful comments and suggestions. We thank seminar and conference participants at the 2016 NBER mid-year DSGE meeting, Richmond Fed, Carleton University, American Economic Association (Philadelphia 2018), Canadian Economic Association (Ottawa 2016), European Economic Association (Geneva 2016), American Economic Association (Boston 2015), Mid-West Macro Meeting (Missouri 2014), University of Dortmund, DIW Berlin and Universities of Manchester and Sheffield for useful comments. We are grateful to Giorgio Primiceri and Eric Sims for providing computer codes and John Fernald for useful conversations on the construction of the TFP series. All remaining errors are our own. John Tsoukalas and Francesco Zanetti gratefully acknowledge financial support from the Leverhulme Trust Research Project Grant and Christoph Görtz acknowledges financial support from a British Academy/Leverhulme grant.

† Go to https://doi.org/10.1257/mac.20170066 to visit the article page for additional materials and author disclosure statements or to comment in the online discussion forum.

[1] See Gilchrist and Zakrajšek (2012) and Philippon (2009).

that provide complementary readings on the significance and dynamics of news shocks. We use a vector autoregression (VAR) model enriched with credit spread indicators and measures of credit supply conditions to isolate two novel stylized facts.

First, a TFP news shock identified from the VAR model as the shock that explains the majority of the variance in TFP in a long horizon, generates an immediate and significant decline of key credit spread indicators along with a broad-based increase in economic activity in anticipation of the future improvement in TFP. The decline of the credit spread indicators is a robust finding that holds across alternative specifications of the VAR model and different identification methods.[2] We focus on the dynamics of the highly informative credit spread indicator introduced by Gilchrist and Zakrajšek (2012) (GZ spread), and its two components, namely, the expected default component and excess bond premium component. We find that the decline in the GZ spread is primarily driven by a decline in the excess bond premium, not a fall in the expected default component of the GZ spread, which exhibits an insignificant response. The excess bond premium is interpreted by Gilchrist and Zakrajšek (2012) as an indicator of the capacity of intermediaries to extend loans or more generally the overall credit supply conditions in the economy.

Second, we independently apply an agnostic methodology proposed by Uhlig (2003) to identify a single shock that explains the majority of the unpredictable movements in the excess bond premium. This exercise reveals a striking fact: the single shock, identified from this procedure, generates dynamics that resemble qualitatively and quantitatively those produced by a TFP news shock. Specifically, it generates a broad-based increase in economic activity, a delayed build-up of TFP toward a new permanently higher level, and an immediate and strong decline in the excess bond premium. Moreover, the robust decline in inflation helps to clearly distinguish this shock from a conventional financial shock. The shock we recover from this agnostic identification explains approximately two-thirds of the forecast error variance in the excess bond premium over business cycle frequencies. The two novel stylized facts we document provide robust evidence on the importance of movements in credit spread indicators for the propagation of news shocks and motivate our modeling approach in the second part of the paper.

We investigate the link between credit spread indicators and news shocks using a two-sector dynamic stochastic general equilibrium (DSGE) model whose microfoundations enable the underpinning of the mechanisms for the propagation of news shocks.[3] To this end, we introduce financial frictions in the supply side of finance via leveraged banks similar to Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). Furthermore, we introduce frictions in the adjustment of financial claims that fund capital acquisitions. These financial claims are held by banks in the form of debt, and by households in the form of corporate equity. This approach

[2] Our baseline identification scheme follows the approach in Francis et al. (2014). We discuss robustness to alternative identification approaches in Section IC.

[3] An important motivation for considering a two-sector economy is the recent evidence in Basu et al. (2013), which suggests that sector-specific technological changes have different macroeconomic effects. The consumption- and investment-goods-producing sectors are therefore subject to sector-specific TFP technologies, in line with this recent evidence.

is motivated by earlier work in corporate investment and finance (see Gomes 2001; Altinkiliç and Hansen 2000; Hennessy and Whited 2007, among others) that identifies significant issuance costs for equity and debt. We apply the DSGE model directly to post-1984 US real and financial data to estimate the model's parameters with Bayesian methods. We produce dynamic responses and business cycle statistics that suggest TFP news shocks are important drivers of business cycle fluctuations, accounting for approximately 52 percent and 50 percent of the variance in output and hours respectively. The DSGE model provides a compelling structural narrative for the propagation mechanism and the empirical relevance of TFP news shocks and allows to assess the strength of the financial amplification channel by switching it off. The presence of leveraged financial intermediaries delivers a strong amplification of news shocks due to the feedback loop between leveraged bank equity and corporate bond prices. Financial intermediaries hold claims to productive capital in their portfolios in the form of corporate bonds. When the price of corporate bonds increases, their equity value increases and their leverage constraint eases, making the excess premium on holding debt to fall and their balance sheet to expand. This dynamic generates a further rise in the demand for bonds and a further rise in the price of bonds. The demand for bonds is thus amplified by leverage, bidding up the bond prices relative to a standard New Keynesian model without financial frictions. The amplification delivers a strong lending and investment phase and a strong economy-wide boom. In contrast, in the standard DSGE model without financial frictions, amplification is weak. It predicts that TFP news shocks account for a maximum of 14 percent and 18 percent of the variance in output and hours worked, respectively, much in line with the existing estimated DSGE literature.

To formally assess whether the financial channel conforms the dynamic responses of the variables to TFP news shocks in the DSGE and VAR methods, we perform a Monte Carlo experiment. We compare the impulse responses to an aggregate TFP news shock from the empirical VAR model with those estimated from the same VAR model on artificial data generated using posterior estimates of the DSGE model. We find that empirical VAR responses of key macroeconomic aggregates (including corporate bond spreads) are consistent with the VAR responses estimated from artificial model data. The experiment shows that accounting for financial frictions leads the two methodologies *independently implemented* to reach similar conclusions on the dynamic effects of TFP news shocks.

To appraise the quantitative relevance of news shocks between the two methods, we undertake a comparison in the shares of the forecast error variance of key macro aggregates. The VAR and DSGE methodologies provide a very consistent picture on the importance of TFP news shocks: for example, at business cycle frequencies (6 to 32 quarters), the VAR model establishes that TFP news shocks account for between 44 percent to 69 percent of the variance in output and between 36 percent to 45 percent of the variance in hours worked. The DSGE model finds the same shocks account for between 33 percent to 51 percent of the variance in output and between 33 percent to 46 percent of the variance in hours worked. Taken together, these findings suggest that both methodologies find TFP news shocks an important source of business cycles in the Great Moderation era and hence provide support for the traditional "news view" of aggregate fluctuations.

Our study is related to the large research agenda on the role of news shocks for macroeconomic fluctuations. The literature shows substantial disagreement over the propagation mechanism and empirical plausibility of TFP news shocks.[4] In the context of the VAR methodology, e.g., Beaudry and Portier (2006); Beaudry and Lucke (2010); Beaudry, Nam, and Wang (2012); and Görtz, Gunn, and Lubik (2022) find that TFP news shocks account for a major fraction of macroeconomic fluctuations whereas Barsky and Sims (2011) and Forni et al. (2014) detect a limited role of TFP news shocks to aggregate fluctuations. More recently, Ben Zeev and Khan (2015) identify investment-specific news shocks as a major driver of US business cycles, a finding supportive of the technology news interpretation of aggregate fluctuations. In the context of the DSGE methodology, Schmitt-Grohé and Uribe (2012) estimate a real business cycle model and find that TFP news shocks are unimportant drivers of business cycle fluctuations, but suggest alternative nonstructural news shocks, such as wage markup news shocks, are important drivers of fluctuations. Fujiwara, Hirose, and Shintani (2011) and Khan and Tsoukalas (2012) reach a similar conclusion in models with nominal rigidities. Christiano, Motto, and Rostagno (2014) estimate a DSGE model that emphasizes borrowers' credit frictions and find an empirical role for news shocks in the riskiness of the entrepreneurial sector. Görtz and Tsoukalas (2017) find empirical relevance for TFP news shocks highlighting financial frictions.

Our contribution to this literature is twofold. First, using VAR methods, we document new facts that speak to the relevance and importance of credit supply frictions for the propagation of news shocks. We establish a tight link between TFP news shocks and shocks (identified independently from news shocks) that drive the majority of unpredictable movements in credit spread indicators suggesting the latter are important asset prices that reflect future economic news. Second, our DSGE estimation offers a quantification of financial frictions by estimating parameters that control rigidities in the adjustment of debt and equity, and a parameter which controls the elasticity between the corporate bond spread and the leverage constraint of banks. This is crucial as the model relies on frictions in financial markets as key amplification mechanisms to assign significant empirical relevance to TFP news shocks. Our model with financial frictions is consistent with the VAR narrative and therefore a very good first step in understanding the propagation of news shocks. By focusing on financial frictions, our study therefore suggests that different methodologies can result in consistent readings and provide a unified view for the macroeconomic effects of TFP news shocks.

The remainder of the paper is organized as follows. Sections I and II describe the VAR and DSGE analysis, respectively. Section III reconciles the differences between the DSGE and the VAR findings and Section IV concludes.

[4] The review article by Beaudry and Portier (2014) provides an extensive discussion on the literature.

I. VAR Analysis

This section describes the VAR model, the data and the methodology used for the estimation, and the results from the VAR analysis.

A. *The VAR Model*

Consider the following reduced-form VAR(p) model,

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

where y_t is an $n \times 1$ vector of variables of interest, $A(L) = I + A_1 L + A_2 L^2 + \ldots + A_p L^p$ is a lag polynomial, $A_1, A_2, \ldots, A_p$ are $n \times n$ matrices of coefficients and, finally, u_t is an error term with $n \times n$ covariance matrix Σ. Define a linear mapping between reduced form, u_t, and structural errors, ε_t,

$$u_t = B_0 \varepsilon_t. \tag{2}$$

We can then write the structural moving average representation as

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

where $C(L) = A(L) B_0$, $\varepsilon_t = B_0^{-1} u_t$, and the matrix B_0 satisfies $B_0 B_0' = \Sigma$. The B_0 matrix may also be written as $B_0 = \tilde{B}_0 D$, where $\tilde{B}_0$ is any arbitrary orthogonalization of Σ and D is an orthonormal matrix ($DD' = I$).

The h step ahead forecast error is

$$y_{t+h} - E_{t-1} y_{t+h} = \sum_{\tau=0}^{h} A_\tau \tilde{B}_0 D \varepsilon_{t+h-\tau}. \tag{4}$$

The share of the forecast error variance of variable i attributable to shock j at horizon h is then

$$V_{i,j}(h) = \frac{e_i'\left(\sum_{\tau=0}^{h} A_\tau \tilde{B}_0 D e_j e_j' D' \tilde{B}_0' A_\tau'\right) e_i}{e_i'\left(\sum_{\tau=0}^{h} A_\tau \Sigma A_\tau'\right) e_i} = \frac{\sum_{\tau=0}^{h} A_{i,\tau} \tilde{B}_0 \gamma \gamma' \tilde{B}_0' A_{i,\tau}'}{\sum_{\tau=0}^{h} A_{i,\tau} \Sigma A_{i,\tau}'}, \tag{5}$$

where e_i denotes selection vectors with one in the i-th position and zeros elsewhere. The e_j vectors pick out the j-th column of D, denoted by γ. $\tilde{B}_0 \gamma$ is an $n \times 1$ vector corresponding to the j-th column of a possible orthogonalization and can be interpreted as an impulse response vector. In the following section, we discuss the estimation and identification methodology that yields an estimate for the TFP news shock from the VAR model.

B. *VAR Estimation*

We estimate the VAR model using quarterly US data on a Great Moderation sample for the period 1984:I–2017:I.[5] To estimate the VAR model we use five lags with a Minnesota prior and compute confidence bands by drawing from the posterior—details are given in the online Appendix. A key input is an observable measure of TFP and for this purpose we use the utilization-adjusted aggregate TFP measure provided by John Fernald of the San Francisco Fed. The methodology used to compute the TFP measure is based on the growth accounting methodology in Basu, Fernald, and Kimball (2006) and corrects for unobserved capacity utilization, described in Fernald (2014). The time series included in the VAR enter in levels, consistent with the treatment in the empirical VAR literature (e.g., Barsky and Sims 2011; Beaudry and Portier 2004, 2006, 2014). Details about the data are provided in the online Appendix. The data used in the VAR and DSGE analysis are from the St. Louis Federal Reserve Bank (Federal Reserve Bank of St. Louis 2017); the Federal Reserve Board (Favara et al. 2016); the Wharton Research Data Services (Wharton Research Data Services 2018); Shiller (2017); and Fernald (2014).

To identify the TFP news shock from the VAR model, we adopt the identification scheme of Francis et al. (2014) (referred to as the Max Share method). The Max Share method recovers the news shock by maximizing the variance of TFP at a specific long but finite horizon (we set the horizon to 40 quarters) and imposes a zero impact restriction on TFP conditional on the news shock.

C. *Results from the VAR Model*

TFP News Shock and Credit Market Indicators.—We begin our exploration with a VAR specification that estimates responses to a TFP news shock. Our set of observables allows us to examine responses to the GZ spread constructed by Gilchrist and Zakrajšek (2012).[6] The GZ spread indicator uses firm level information from corporate senior unsecured bonds traded in the secondary market, controls for the maturity mismatch between corporate and treasuries, and spans the entire spectrum of issuer credit quality (from investment grade to below investment grade).

Figure 1 displays Impulse Response Functions (IRFs) from a VAR featuring aggregate TFP, output, consumption, hours, GZ spread, the S&P 500, and inflation (log change in GDP deflator). Several interesting findings emerge. First, TFP rises in a delayed fashion, and it becomes significantly different from zero after approximately three years. This pattern shows that the identification scheme produces empirically plausible news shocks, as discussed in Beaudry and Portier (2014). Second, the VAR-identified TFP news shock creates a boom today: output, consumption, and hours increase significantly on impact, and they display hump-shaped dynamics.

[5] Galí and Gambetti (2009), among others, document significant changes in the comovement properties of important macro-aggregates before and after the mid-1980s, and Jermann and Quadrini (2009) highlight changes in moments of financial sector variables in the mid- and late-1980s. We report robustness of our findings to end date (excluding the Great Recession period) of the sample in Görtz, Tsoukalas, and Zanetti (2022).

[6] We have also examined the popular BAA spread (difference between the yield of a BAA rated corporate bond and a ten-year Treasury) and found results that are very similar to the ones reported in the main body of the paper.

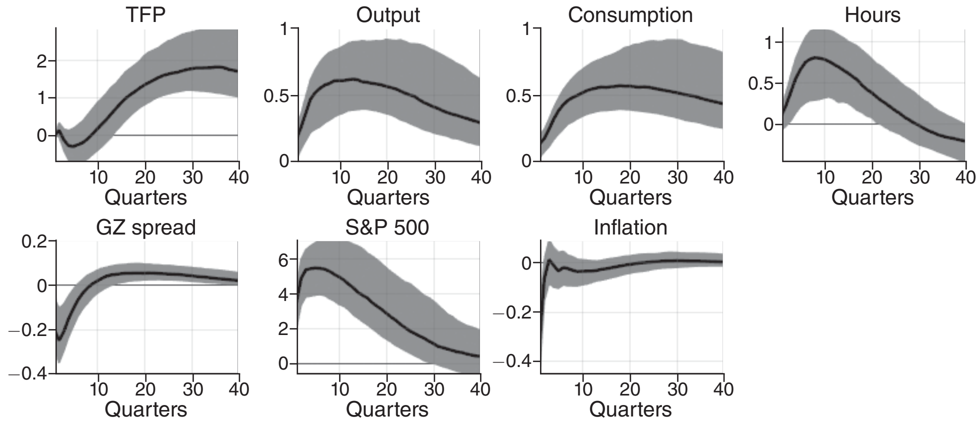

Figure 1. TFP News Shock

Notes: Impulse responses to a TFP news shock from a seven-variable VAR. The shaded gray areas are the 16 percent and 84 percent posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Third, the GZ spread declines significantly, suggesting that corporate bond markets anticipate movements in future TFP, which is consistent with an economic expansion induced by an increase in lending. The behavior of the GZ spread is a novel stylized fact that, to the best of our knowledge, no previous studies have documented. Further, the S&P 500 also increases in anticipation of the future rise in TFP, consistent with the work by Beaudry and Portier (2006) that finds the stock market captures changes in agents' expectations of future economic outlook. Finally, the news shocks are associated with a short-lived decline in inflation. The decline in inflation is a very robust finding in the empirical news shock literature with VAR methods (see Barsky and Sims 2011; Barsky, Basu, and Lee 2015; Cascaldi-Garcia 2019) and at first pass it may appear puzzling, given the "demand-like" nature of news shocks, i.e., a broad-based increase in activity in the absence of a productivity improvement in the short term. We discuss this finding in Section III and note that the New Keynesian model we estimate in Section II may partly rationalize the behavior of inflation in response to a news shock.

TFP News Shock, Excess Bond Premium and Balance Sheet Conditions.— Evidence by Gilchrist and Zakrajšek (2012) strongly suggests that the GZ spread is superior, relative to conventional indicators such as the BAA spread, in terms of forecasting future economic activity. The GZ spread can be usefully decomposed into a component capturing cyclical changes in default risk (i.e., expected defaults), and a component that measures cyclical changes in the relationship between default risk and credit spreads, the *excess bond premium* (EBP). Importantly, Gilchrist and Zakrajšek (2012) provide evidence to indicate that over the sample 1985–2010, the excess bond premium contains most of the predictive content of the GZ spread for various measures of economic activity. We further examine the role of balance sheet

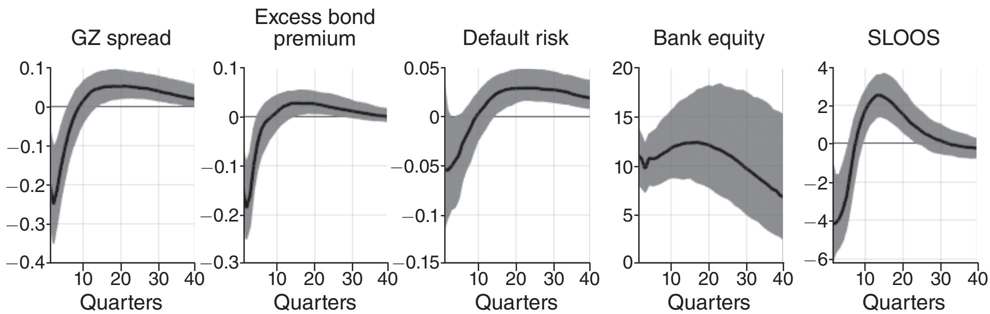

Figure 2. TFP News Shock: Financial Responses

Notes: Impulse responses to a TFP news shock from seven-variable VARs. The estimated VARs includes the variables shown in Figure 1 where we replace the GZ spread with the shown variables one at a time and re-estimate the VAR. The shaded gray areas are the 16 percent and 84 percent posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

conditions of intermediaries for the propagation of news shocks using two indicators: first, the market value of US commercial bank's equity (henceforth bank equity); and second, the Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS).[7] We examine the behavior of the excess bond premium, default risk, market value of bank equity and indicator of lending standards by replacing each of these indicators in the VAR specification discussed above in place of the GZ spread. Figure 2 displays the results. Our novel finding is that the excess bond premium declines significantly on impact and, similarly to the behavior of the GZ spread, ahead of the future rise in TFP. Notice that the forecasting ability of the excess bond premium as emphasized by Gilchrist and Zakrajšek (2012) is implicitly reflected in the shape of the dynamic responses, given the hump-shaped dynamics of the real activity variables (as shown in Figure 1). Interestingly, the default risk component of the GZ spread is, in contrast to the excess bind premium, not reacting significantly in response to the news shock. This observation suggests that the variation in the GZ credit spread conditional on the news shock is driven by factors mostly related to credit supply conditions. We provide more evidence for this link below.[8]

The dynamic responses displayed in Figure 2 suggest an immediate, strong, and significant positive response of bank equity. The response of bank equity is consistent with the notion that it reflects increased profitability and/or higher asset valuation in the balance sheet of intermediaries. The response of the SLOOS variable suggests an immediate and significant relaxation of lending standards, which persists for about two years. Both sets of findings related to the joint response of the

[7] The market value of equity is aggregated from all publicly listed financial institutions provided by the Center for Research in Securities Prices (CRSP) (online Appendix Section 2 provides details on the data). The SLOOS measures the net percentage of domestic respondents tightening standards for commercial and industry loans. We use the net percentage applicable for loans to medium and large firms. Specifically the net percentage measures the fraction of banks that reported having tightened ("tightened considerably" or "tightened somewhat") minus the fraction of banks that reported having eased ("eased considerably" or "eased somewhat"). We focus on the survey that asks participating banks to report changes in lending standards for commercial and industrial loans.

[8] We do not show the IRFs to the remaining variables in the VARs used to generate Figure 2 in order to conserve space since the IRFs are quantitatively similar to those displayed in Figure 1.

excess bond premium, bank equity and lending standards are consistent with the evidence reported in Gilchrist and Zakrajšek (2012), where higher profitability of the US financial corporate sector is associated with a reduction in the excess bond premium. Taken together, these findings support the hypothesis that balance sheet and more generally credit supply conditions are an important transmission channel for TFP news shocks.

What Are the Shocks that Move Credit Spread Indicators?—The preceding evidence suggests that credit spread indicators may be capturing a transmission mechanism for news shocks that is grounded on credit market frictions. To provide further evidence for the link between news shocks and the excess bond premium we proceed to independently identify shocks that explain the majority of the unforecastable movements in the excess bond premium. Specifically, we proceed to identify, in an agnostic manner, following the methodology proposed by Uhlig (2003), a single shock that maximizes the forecast error variance (FEV) of the excess bond premium (we term it the "max FEV EBP shock") at cyclical frequencies (horizons 6 to 32 quarters). This exercise is similar in spirit to the analysis in Beaudry and Portier (2006) who focus on shocks that explain short-run movements in stock prices and then establish a link between those shocks and TFP news shocks.

Here the goal is to establish the link, if any, between movements in asset prices from the corporate debt market and news shocks. Consider a VAR specification featuring the excess bond premium, output, hours, consumption, TFP, inflation, and the S&P 500 indicator. We find that the max FEV EBP shock identified from this VAR specification explains approximately two-thirds of the forecast error variance (median shares) in the EBP in forecast horizons from 6 to 32 quarters. We then compare the IRFs induced by the max FEV EBP shock with the IRFs induced by the TFP news shock using the same VAR specification. Figure 3 displays the two sets of IRFs. The comparison reveals a striking new finding. The two shocks, independently identified, exhibit very similar dynamic paths, both qualitatively and quantitatively. Both shocks are associated with an immediate increase in activity, and a countercyclical response of the excess bond premium.[9] The similarity in the dynamics of the excess bond premium across the two independent identification exercises is, we think, an important finding since, according to the arguments and evidence in Gilchrist and Zakrajšek (2012), the excess bond premium captures cyclical variations in credit market supply conditions. Adopting this interpretation, a favorable TFP news shock is associated with a reduction in the excess bond premium and a relaxation of credit market supply conditions that coincides with a boom in activity, leading to the hypothesis we advance in this paper: balance sheet conditions of financial intermediaries matter for the propagation of news shocks. Importantly, the max FEV EBP shock is a relevant business cycle shock in a quantitative sense as

[9] Notice that in the VAR with the agnostic identification that seeks for the max FEV EBP shock, there is no zero impact restriction associated with the IRF of TFP, hence, TFP can freely move on impact of this shock. Nevertheless, the IRF confidence bands for TFP in this identification suggest that this positive impact response is not significantly different from zero. In fact, TFP rises significantly above zero at approximately 20 quarters.

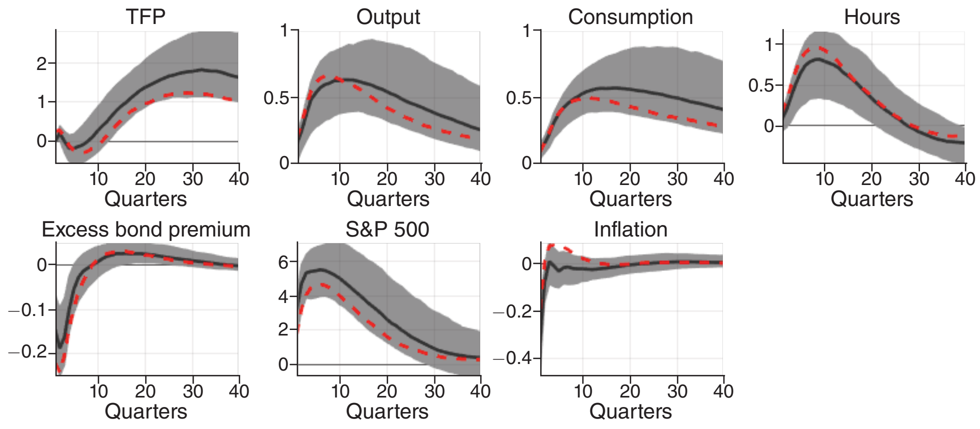

FIGURE 3. TFP NEWS SHOCK AND MAX FEV EBP SHOCK

Notes: Median IRFs to a TFP news shock (solid black line) and a max-EBP shock (dashed red line) from seven-variable VARs. The shaded gray areas are the 16 percent and 84 percent posterior bands of the TFP news shock generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

this shock explains more than 64 percent of the FEV in output and hours (median shares).[10, 11]

It is interesting to note that recent work in Queralto (2020) and Moran and Queralto (2018) emphasize demand-driven factors behind medium-term dynamics in TFP. Under this interpretation financial shocks influence business innovation activities and consequently future TFP. To address a concern that our identification strategy confounds TFP news with financial shocks we proceed to identify, within the same VAR framework above, additional to a TFP news shock, a financial shock as the innovation to the EBP. This analysis can distinguish a TFP news shock that moves future TFP, from a financial shock that moves both current and future TFP. To conserve space, we report these dynamic responses in the online Appendix: following a positive financial shock that generates a decline in EBP, in the short run, activity increases, and TFP rises with a long delay in the future—indeed very similar to the IRFs displayed by the max EBP shock in Figure 3. The important insight of this analysis is the fact that the behavior of inflation is critical to be able to clearly distinguish a financial shock from a news TFP shock. Conditional on a financial

[10] To conserve space the contribution of the max FEV EBP shock to the FEV of all variables included in the VAR is shown in the online Appendix.

[11] Our findings are robust in a number of dimensions. In the online Appendix we show responses based on the same methodology used to generate Figure 3, but we use the GZ spread as our target variable and compare the max FEV GZ spread shock to the TFP news shock identified using the same VAR information. Moreover our results are robust to alternative news shock identification approaches which are described in detail in the online Appendix. Further, to protect against the possibility that our results are driven by the financial crisis years (which were characterized by large, albeit short-lived, swings in credit spreads) or the "Great Recession" more generally we have repeated the VAR analysis excluding this part of the sample. The results are reported in the online Appendix and suggest that all of our VAR findings are robust to this consideration.

shock, inflation comoves with activity.[12] In contrast, as discussed above, conditional on a TFP news shock, inflation declines concurrently with an increase in activity.

II. DSGE Analysis

This section discusses the DSGE model, the data, the methodology used for the estimation, and the results from the DSGE analysis.

A. *The Model*

Below, we describe the parts of the model related to the goods-producing sectors, households, the financial sector, the exogenous disturbances, and the arrival of information. The online Appendix provides a description of the complete model.

Intermediate and Final Goods Production.—A monopolist produces consumption and investment-specific intermediate goods according to the production technologies

$$C_t(i) = \max\left[a_{lt} A_t \left(L_{C,t}(i)\right)^{1-a_c} \left(K_{C,t}(i)\right)^{a_c} - A_t V_t^{\frac{a_c}{1-a_i}} F_C, 0\right]$$

and

$$I_t(i) = \max\left[v_{lt} V_t \left(L_{I,t}(i)\right)^{1-a_i} \left(K_{I,t}(i)\right)^{a_i} - V_t^{\frac{1}{1-a_i}} F_I, 0\right],$$

respectively. The variables $K_{x,t}(i)$ and $L_{x,t}(i)$ denote the amount of capital and labor services rented by firm i in sector $x = C, I$, and the parameters $(a_c, a_i) \in (0,1)$ denote capital shares in production.[13] The variables A_t and V_t denote the (nonstationary) level of TFP in the consumption and investment sector, respectively, and the variables $z_t = ln(A_t/A_{t-1})$ and $v_t = ln(V_t/V_{t-1})$ denote (stationary) stochastic growth rates of TFP in the consumption and investment sector, respectively. The variables a_{lt}, v_{lt}, denote the stationary level of TFP in the consumption and investment sector, respectively. To facilitate the exposition, the processes for the exogenous disturbances are described later in Section IIA. Intermediate goods producers set prices according to Calvo (1983) contracts.

Perfectly competitive firms manufacture final goods, C_t and I_t, in the consumption and investment sector by combining a continuum of intermediate goods in each sector, $C_t(i)$ and $I_t(i)$, respectively, according to the production technologies

$$C_t = \left[\int_0^1 \left(C_t(i)\right)^{\frac{1}{1+\lambda_{p,t}^C}} di\right]^{1+\lambda_{p,t}^C} \quad \text{and} \quad I_t = \left[\int_0^1 \left(I_t(i)\right)^{\frac{1}{1+\lambda_{p,t}^I}} di\right]^{1+\lambda_{p,t}^I},$$

[12] The dynamics following a financial shock are therefore consistent with the empirical VAR analysis in Gilchrist and Zakrajšek (2012).

[13] As in Christiano, Eichenbaum, and Evans (2005), the presence of fixed costs in production in both sectors (i.e., $F_C > 0$ and $F_I > 0$) leads to zero profits along the nonstochastic balanced growth path thereby the analysis abstracts from entry and exit of intermediate good producers. Fixed costs grow at the same rate of sectoral output to retain relevance for the firms' profit decisions.

where the exogenous elasticities $\lambda_{p,t}^{C}$ and $\lambda_{p,t}^{I}$ across intermediate goods in each sector determine the (sectoral) price markup over marginal cost. Similar to the standard New Keynesian framework, prices of final goods in each sector ($P_{C,t}$ and $P_{I,t}$) are CES aggregates of intermediate goods prices. The online Appendix provides details on price-setting decisions of the intermediate goods producers.

Households.—As in Gertler and Karadi (2011), households comprise two types of members, workers of size $1-f$ and bankers of size f. Each worker j supplies diversified labor in return for a wage. Effectively, households own the intermediaries managed by bankers, but they do not own the deposits held by the financial intermediaries. Perfect risk sharing exists within each household. The proportion of workers and bankers remains constant over time. However, members of the households are allowed to switch occupations to avoid bankers having to fund investments from their own capital without having to access credit. Bankers become workers in the next period with probability $(1-\theta_B)$ and transfer the retained earnings to households. Households supply startup funds to workers who become bankers. We moreover enrich this setup to allow workers in each family to save in financial claims that finance capital acquisitions from capital services producers. To make this operational, we introduce fictitious perfectly competitive money market funds that collect savings from households and buy financial claims from a large number of firms in each sector. Each money market fund specializes in buying claims from the consumption or investment sector only. At the end of each period, money market funds return the proceeds from the claims back to households and a new round begins. Each household maximizes the utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t b_t \left[\ln\left(C_t - hC_{t-1}\right) - \varphi \frac{\left(L_{C,t}(j) + L_{I,t}(j)\right)^{1+\nu}}{1+\nu} \right],$$

where E_0 is the conditional expectation operator at the beginning of period 0, $\beta \in (0,1)$ is the discount factor, and $h \in (0,1)$ is the degree of external habit formation. The inverse Frisch labor supply elasticity is denoted by $\nu > 0$, and the parameter $\varphi > 0$ enables the model to replicate the steady-state level of total labor supply in the data.[14] The variable b_t denotes an intertemporal preference shock. Each household faces the following budget constraint expressed in consumption units

$$(6) \quad C_t + \frac{B_t}{P_{C,t}} + \frac{S_{C,t}^h + S_{I,t}^h}{P_{c,t}} \leq \frac{W_t(j)}{P_{C,t}}\left(L_{C,t}(j) + L_{I,t}(j)\right) + R_{t-1}\frac{B_{t-1}}{P_{C,t}} + \frac{R_{C,t-1}^h S_{C,t-1}^h}{P_{C,t}} + \frac{R_{I,t-1}^h S_{I,t-1}^h}{P_{C,t}} - \frac{T_t}{P_{C,t}} + \frac{\Psi_t(j)}{P_{C,t}} + \frac{\Pi_t}{P_{C,t}},$$

[14] Note that consumption is not indexed by (j) because perfect risk sharing leads to similar asset holding across members of the household.

where $S^h_{C,t}$ and $S^h_{I,t}$ are financial (equity) claims in the consumption and investment sectors respectively purchased from households through the sector-specialized money market funds that pay a nominal return per unit of equity equal to $R^h_{C,t}$ and $R^h_{I,t}$, respectively. The variable B_t denotes holdings of risk-free bank deposits, Ψ_t is the net cash flow from the household's portfolio of state contingent securities, T_t is lump sum taxes, R_t, is the (gross) nominal interest rate paid on deposits, Π_t is the net profit accruing to households from ownership of all firms, and $P_{C,t}$ is the consumption deflator. The wage rate, W_t, is identical across sectors due to perfect labor mobility.

The households first-order condition for the purchase of financial claims from capital services producing firms in sector $x = C, I$ is

$$1 = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R^h_{x,t} P_{c,t}}{P_{c,t+1}}. \tag{7}$$

Household's return, $R^h_{x,t}$, related to the acquisition of financial claims from capital services producers will be formalized in the following section.

As in Erceg, Henderson, and Levin (2000), each household sets the wage according to Calvo contracts. The desired markup of wages over the household's marginal rate of substitution (or wage markup), $\lambda_{w,t}$, follows an exogenous stochastic process.

Production of Capital Goods.—

Production of Physical Capital: We assume that significant reallocation costs between sectors lead to immobile sector-specific capital.[15] Capital producers in each sector $x = C, I$ manufacture capital goods using a fraction of investment goods from final-goods producers and undepreciated capital from capital-services producers, subject to investment adjustment costs (IAC), similar to Christiano, Eichenbaum, and Evans (2005). Solving the optimization problem of capital producers yields the standard capital accumulation equation

$$\bar{K}_{x,t} = (1 - \delta_x)\bar{K}_{x,t-1} + \mu_t\left(1 - S\left(\frac{I_{x,t}}{I_{x,t-1}}\right)\right) I_{x,t}, \tag{8}$$

for $x = C, I$. The parameter δ_x denotes the sectoral depreciation rate, the function $S(I_{x,t}/I_{x,t-1})$ captures IAC and has standard properties—i.e., $S(\cdot)$ satisfies the following conditions: $S(1) = S'(1) = 0$ and $S''(1) = \kappa > 0$. Finally, the variable μ_t denotes the marginal efficiency of investment (MEI) shock, as in Justiniano, Primiceri, and Tambalotti (2010).

Production of Capital Services and Finance Sources: The producers of capital services purchase capital from physical capital producers and choose the utilization rate to convert it into capital services. This purchase is financed by issuing claims on physical capital and producers have two sources of finance. As in Gertler and

[15] Ramey and Shapiro (2001) find strong evidence of large reallocation costs between sectors. Boldrin, Christiano, and Fisher (2001); Ireland and Schuh (2008); Huffman and Wynne (1999); and Papanikolaou (2011) establish that constrained factor mobility improves the performance of theoretical models of the business cycle to replicate movements in aggregate fluctuations.

Karadi (2011), capital services producers issue claims to financial intermediaries to finance the purchase of capital at the end of each period, as described in the next subsection. Moreover—following the description of households—the producers can issue claims on physical capital to households and these purchases are facilitated through the money market funds. Capital services producers rent capital services to intermediate-goods producers that operate in a perfectly competitive market for a rental rate equal to $R^K_{x,t}/P_{C,t}$ per unit of capital. At the end of period $t+1$, they sell the undepreciated portion of capital to physical capital producers. The utilization rate, $u_{x,t}$, transforms physical capital into capital services according to

$$K_{x,t} = u_{x,t}\bar{K}_{x,t-1},$$

for $x = C, I$ and subjects to a cost $a_x(u_{x,t})$ per unit of capital. The function $a_x(u_{x,t})$ has standard properties—i.e., in steady state, $u = 1$, $a_x(1) = 0$ and $\chi_x \equiv (a''_x(1)/a'_x(1))$ denotes the cost elasticity.

Producers of capital services adjust capital acquisitions by adjusting financial claims to households and financial intermediaries, $S^h_{x,t}$ and $S_{x,t}$, respectively, at the nominal price $Q^h_{x,t}$ and $Q_{x,t}$, respectively. The total value of capital acquired, $Q^T_{x,t}\bar{K}_{x,t}$, equals the total value of financial claims held by households and financial intermediaries against this capital

$$Q^T_{x,t}\bar{K}_{x,t} = Q^h_{x,t}S^h_{x,t} + Q_{x,t}S_{x,t}. \tag{9}$$

Capital services producers in sector $x = C, I$ choose utilization and quantity of financial claims to households and financial intermediaries to maximize expected profits,

$$\max_{u_{x,t}, S^h_{x,t}, S_{x,t}} E_0 \sum_{t=0}^{\infty} \beta^t \Lambda_t \Bigg\{ \frac{R^K_{x,t}}{P_{C,t}} u_{x,t}\bar{K}_{x,t-1} - a_x(u_{x,t})\,\bar{K}_{x,t-1} A_t V_t^{\frac{a_c-1}{1-a_i}}$$
$$- \left(\gamma^h S^h_{x,t} + \gamma S_{x,t}\right) A_t V_t^{\frac{a_c-1}{1-a_i}}$$
$$- \Gamma\left[\left(\frac{S^h_{x,t}}{s^h_x V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right), \left(\frac{S_{x,t}}{s_x V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right)\right] A_t V_t^{\frac{a_c}{1-a_i}} \Bigg\},$$

subject to the constraint (9).

Adjusting the level of financial claims is costly. First, adjustment entails fixed costs per unit of financial claim, $S^h_{x,t}$ and $S_{x,t}$, controlled by parameters γ^h and γ respectively (these parameters will be pinned down by steady-state relationships as described in the online Appendix). Second, it also involves adjustment costs captured by the additively separable function $\Gamma(\cdot)$.[16] Our approach is largely inspired

[16] In this function, $s^h_x = S^h_x / V^{\frac{1}{1-a_i}}$ and $s_x = S_x / V^{\frac{1}{1-a_i}}$ denote the stationarized steady-state expressions for claims on capital and g_v is the steady-state growth rate of V_t (also the rate of growth of investment and capital). This implies that in the stationarized economy the function $\Gamma(0,0)$ equals 0 in the steady state. The stationary economy is described in detail in the online Appendix.

by Gomes (2001); Cooley and Quadrini (2001); and Hennessy and Whited (2007) who specify fixed, linear, and quadratic issuance costs for equity, and by Altinkiliç and Hansen (2000) who show that debt and equity issuance costs have fixed and convex cost components. Moreover, Leary and Roberts (2005) provide evidence to suggest capital structure choice is subject to adjustment costs.

Formally, the function has the following properties: $\Gamma(0,0) = 0$, $\Gamma_{S_x^h}(0,0) = \Gamma_{S_x}(0,0) = 0$, $\Gamma_{S_x^h,S_x^h}(0,0) = \kappa^h > 0$, $\Gamma_{S_x,S_x}(0,0) = \kappa^B > 0$ and $\Gamma_{S_x^h,S_x}(0,0) = \Gamma_{S_x,S_x^h}(0,0) = 0$, where subscripts denote the marginal cost of $\Gamma(\cdot)$. Intuitively, all capital acquisitions by capital services firms are financed from either banks or households. Any adjustment in the financing mix by deviating from the steady-state levels of debt or equity entails costs.[17] Note, that the key parameters that capture the (marginal) rigidities in the adjustment of sources of funds are denoted κ^h and κ^B and they are meant to capture the fact that firms often adjust equity and debt only slowly—one reason may be the well-documented phenomenon of dividend smoothing (see Leary and Michaely 2011 and references therein). Our approach to modeling financial frictions is parsimonious. We do not explicitly model agency costs associated with the choice of debt and equity which is beyond the scope of the paper. Our approach is informed by and is similar to Jermann and Quadrini (2012) who capture equity payout costs in a reduced form way in a general equilibrium model.

The first-order conditions of this problem are

$$\beta E_t \frac{\Lambda_{t+1}}{\Lambda_t}\left[\frac{R^K_{x,t+1}}{P_{C,t+1}} u_{x,t+1} \frac{Q^h_{x,t}}{Q^T_{x,t}} - a_x\big(u_{x,t+1}\big) A_{t+1} V_{t+1}^{\frac{a_c-1}{1-a_i}} \frac{Q^h_{x,t}}{Q^T_{x,t}}\right] - \gamma^h A_t V_t^{\frac{a_c-1}{1-a_i}} \tag{10}$$
$$- \Gamma_{s_x^h}\left[\left(\frac{S^h_{x,t}}{s_x^h V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right), \left(\frac{S_{x,t}}{s_x V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right)\right] \frac{A_t V_t^{\frac{a_c}{1-a_i}}}{s_x^h V_{t-1}^{\frac{1}{1-a_i}}} = 0,$$

$$\beta E_t \frac{\Lambda_{t+1}}{\Lambda_t}\left[\frac{R^K_{x,t+1}}{P_{C,t+1}} u_{x,t+1} \frac{Q_{x,t}}{Q^T_{x,t}} - a_x\big(u_{x,t+1}\big) A_{t+1} V_{t+1}^{\frac{a_c-1}{1-a_i}} \frac{Q_{x,t}}{Q^T_{x,t}}\right] - \gamma A_t V_t^{\frac{a_c-1}{1-a_i}} \tag{11}$$
$$- \Gamma_{s_x}\left[\left(\frac{S^h_{x,t}}{s_x^h V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right), \left(\frac{S_{x,t}}{s_x V_{t-1}^{\frac{1}{1-a_i}}} - e^{\left(\frac{1}{1-a_i}\right)g_v}\right)\right] \frac{A_t V_t^{\frac{a_c}{1-a_i}}}{s_x V_{t-1}^{\frac{1}{1-a_i}}} = 0,$$

$$\frac{R^K_{x,t}}{P_{C,t}} - a_x'\big(u_{x,t}\big) A_t V_t^{\frac{a_c-1}{1-a_i}} = 0. \tag{12}$$

Equations (10) and (11) equates the marginal benefit (e.g., how much the issuance of an additional claim contributes to larger capital production) to the marginal cost of adjustment (i.e., how much the issuance of an additional claim requires larger capital utilization and entails adjustment costs). In the stationary log-linear versions

[17] Note that since our model abstracts from bankruptcy and distress costs associated with debt we specify the function $\Gamma(\cdot)$ to treat issuance costs with respect to equity and debt symmetrically.

of these equations the adjustment costs for adjusting claims will be captured by the parameters γ, γ^h, κ^B and κ^h. Equation (12) is the optimal condition for capital utilization.

As in Gertler and Karadi (2011) the stochastic return earned by financial intermediaries from financing capital acquisition is equal to

$$(13) \qquad R^B_{x,t+1} = \frac{\frac{R^K_{x,t+1}}{P_{x,t+1}} u_{x,t+1} + Q_{x,t+1}(1-\delta_x) - a_x(u_{x,t+1}) A_{t+1} V_{t+1}^{\frac{a_c-1}{1-a_i}}}{Q_{x,t}}.$$

The analogous return that accrues to household's is given by

$$(14) \qquad R^h_{x,t} = \frac{\frac{R^K_{x,t+1}}{P_{x,t+1}} u_{x,t+1} + Q^h_{x,t+1}(1-\delta_x) - a_x(u_{x,t+1}) A_{t+1} V_{t+1}^{\frac{a_c-1}{1-a_i}}}{Q^h_{x,t}}.$$

Financial Sector.—Financial intermediaries fund the acquisitions of physical capital from capital-services producers using their own equity capital and deposits from households. They lend in specific islands (sectors) and cannot switch between them. Intuitively, this can be justified by appealing to financial market segmentation, where it may be costly to switch markets once you have developed expertise lending to your market.[18] The financial sector in the model follows closely Gertler and Karadi (2011), and we therefore limit the exposition to the key equations and the online Appendix provides the complete set of equations. Three equations encapsulate the key dynamics in the financial sector: the balance sheet identity, the demand for assets that links equity capital with the value of physical capital (i.e., the leverage constraint) and the evolution of equity capital. We describe each of them in turn.

The nominal *balance sheet identity* of a branch that lends to sector $x = C, I$ is

$$(15) \qquad Q_{x,t} P_{C,t} S_{x,t} = N_{x,t} P_{C,t} + B_{x,t},$$

where the variable $S_{x,t}$ denotes the quantity of financial claims on capital services that the producers held by the intermediary, and $Q_{x,t}$ denotes the price per unit of claim. The variable $N_{x,t}$ denotes equity capital (i.e., wealth) at the end of period t, $B_{x,t}$ are households deposits, and $P_{C,t}$ is the price level in the consumption sector.

Financial intermediaries maximize the discounted sum of future equity capital (i.e., the expected terminal wealth). Bankers may abduct funds and transfer them to the household. This moral hazard/costly enforcement problem limits the capacity of financial intermediaries to borrow funds from the households and generates an

[18] Alternatively, we can interpret the financial sector as a single intermediary with two branches, each specializing in providing financing to one sector only, where the probability of lending specialization is equal across sectors and independent across time. Each branch maximizes equity from financing the specific sector. For example, within an intermediary, there are divisions specializing in consumer or corporate finance. The financial sector can be interpreted as a special case of Gertler and Kiyotaki (2010).

endogenous *leverage constraint* that limits the bank's ability to acquire assets. Thus, the equation for the demand of assets is

$$Q_{x,t} S_{x,t} = \varrho_{x,t} N_{x,t}, \tag{16}$$

where the value of assets that the intermediary acquires $(Q_{x,t} S_{x,t})$ depends on equity capital, $N_{x,t}$, and the leverage ratio, $\varrho_{x,t} = \eta_{x,t}/(\lambda_B - \nu_{x,t})$.[19] In the expression above, λ_B (fraction of assets that bankers can divert for personal gain) is the key financial parameter that captures the agency problem between banks and depositors and we will estimate it in Section IIB. Note that when $\varrho_{x,t} > 1$, the leverage constraint (16) magnifies the changes in equity capital on the demand for assets. This amplification turns out to be the critical mechanism to attach an important role to news shocks in the estimated model.

The *evolution of equity capital* is described by the law of motion,

$$N_{x,t+1} = \left(\theta_B \left[\left(R^B_{x,t+1} \pi_{C,t} - R_t\right) \varrho_{x,t} + R_t\right] \frac{N_{x,t}}{\pi_{C,t+1}} + \varpi Q_{x,t+1} S_{x,t+1}\right) \varsigma_{x,t}, \tag{17}$$

where θ_B is the survival rate of bankers, ϖ denotes the fraction of assets transferred to new bankers, $\pi_{C,t+1}$ denotes the gross inflation rate in the consumption sector and $\varsigma_{x,t}$ is an exogenous shock to the bank's equity capital. Gerali et al. (2010) introduce bank equity shocks in a similar way in a credit and banking model of the euro area, but do not estimate the parameters associated with the shocks. Equation (17) shows that equity capital is a function of the excess (leveraged) real returns earned on equity capital of surviving bankers and the value of assets owned by news bankers. Banks earn expected (nominal) returns on assets (i.e., the risk premium) equal to

$$R^S_{x,t} = R^B_{x,t+1} \pi_{C,t+1} - R_t, \tag{18}$$

for $x = C, I$. The leverage constraint (16) entails nonnegative excess returns that vary over time with movements in the equity capital of intermediaries. As in Gertler and Karadi (2011), there are no frictions in the process of intermediation between nonfinancial firms and banks, and therefore we can interpret the financial claims as one-period, state-contingent bonds in order to interpret the excess returns in equation (18) as a corporate bond spread.

Exogenous Disturbances and Arrival of Information.—The model embeds the following exogenous disturbances: sectoral shocks to the growth rate of TFP (z_t, ν_t), sectoral shocks to the level of TFP (a_{lt}, ν_{lt}), sectoral price markup shocks $(\lambda^C_{p,t}, \lambda^I_{p,t})$, wage markup shock $(\lambda_{w,t})$, preference shock (b_t), monetary policy shock $(\eta_{mp,t})$, government spending shock (g_t), MEI (μ_t) shock, and sectoral shocks to financial intermediaries' equity capital $(\varsigma_{C,t}, \varsigma_{I,t})$. Each exogenous disturbance is expressed in log deviations from the steady state as a first-order autoregressive

[19] As shown in the online Appendix, the leverage ratio (i.e., the bank's intermediated assets-to-equity ratio) is a function of the marginal gains of increasing assets, $\nu_{x,t}$ (holding equity constant), increasing equity, $\eta_{x,t}$ (holding assets constant), and the gain from diverting assets, λ_B.

(AR(1)) process whose stochastic innovation is uncorrelated with other shocks, has a zero-mean, and is normally distributed. For the monetary policy shock $(\eta_{mp,t})$, the first-order autoregressive parameter is set equal to zero. The online Appendix provides details on the exogenous disturbances.

The model embeds news shocks to sectoral productivity growth. The productivity growth processes in the consumption and investment sector follow the law of motions

$$(19) \qquad z_t = (1-\rho_z)\, g_a + \rho_z z_{t-1} + \varepsilon_t^z, \quad \text{and} \quad v_t = (1-\rho_v)\, g_v + \rho_v v_{t-1} + \varepsilon_t^v,$$

where the parameters g_a and g_v are the steady-state growth rates of the two TFP processes above, and $\rho_z, \rho_v \in (0,1)$ determine their persistence.

The representation of news shocks is standard and follows, for example, Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012). The stochastic innovations in the exogenous disturbances in (19) are defined as

$$\varepsilon_t^z = \varepsilon_{t,0}^z + \varepsilon_{t-4,4}^z + \varepsilon_{t-8,8}^z + \varepsilon_{t-12,12}^z, \text{ and } \varepsilon_t^v = \varepsilon_{t,0}^v + \varepsilon_{t-4,4}^v + \varepsilon_{t-8,8}^v + \varepsilon_{t-12,12}^v,$$

where the first component, $\varepsilon_{t,0}^x$, is unanticipated (with $x = z, v$) whereas the components $\varepsilon_{t-4,4}^x$, $\varepsilon_{t-8,8}^x$, and $\varepsilon_{t-12,12}^x$ are anticipated and represent news about period t that arrives 4, 8, and 12 quarters ahead, respectively. As conventional in the literature, the anticipated and unanticipated components for sector $x = C, I$ and horizon $h = 0, 1, \ldots, H$ are *i.i.d.* with distributions $N(0, \sigma_{z,t-h}^2)$ and $N(0, \sigma_{v,t-h}^2)$ that are uncorrelated across sector, horizon, and time. Our choice to consider 4-, 8-, and 12-quarter-ahead sector-specific TFP news is guided by the desire to limit the size of the state space of the model while being flexible enough to allow the news processes to accommodate revisions in expectations.

Model Summary.—The model builds on Görtz and Tsoukalas (2017), one of the few existing DSGE models that can generate empirical relevance of TFP news shocks, with several notable innovations. These innovations allow us to quantify the overall degree of financial frictions through the lens of Bayesian estimation of the model.[20]

[20] First, we extend the model to allow households to directly finance capital acquisition by capital services producers. These claims can be interpreted as corporate equity. Covas and Den Haan (2011) emphasize the importance of equity finance over the business cycle. Thus, capital services firms have two sources of financing capital acquisitions available to them, one from banks in the form of corporate bonds (debt), and one directly from households in the form of corporate equity. We allow them to optimally choose the use between bonds and equity subject to rigidities in the adjustment of financial claims and estimate adjustment cost parameters that determine the degree of rigidities. Second, we also estimate the parameter that captures the limited enforcement problem between banks and depositors in the Gertler and Karadi (2011) setup. Third, and consistent with the modeling innovation we introduce, we use a larger set of observables, including the relative price of investment and corporate equity, and estimate the model over a longer time horizon beginning from the onset of the Great Moderation. Fourth, we introduce financial shocks that compete with news shocks in the estimation. All these additional features allow for a more precise comparison with state-of-the-art estimated DSGE models and previous findings in the literature on the sources of business cycles.

Our choice to use a two-sector model is three-fold. First, the methodology to measure aggregate TFP described in Fernald (2014) is based on sectoral TFP data. The equation is

$$dTFP_{agg,t} \;=\; w_{i,t}\, dTFP_{i,t} + \left(1 - w_{i,t}\right) dTFP_{c,t}, \tag{20}$$

where the variables $dTFP_{agg}$, $dTFP_i$, and $dTFP_c$ denote (utilization-adjusted) TFP growth rates in aggregate, investment- and consumption-specific sectors, respectively, and the coefficient w_i denotes the share of the investment sector, expressed in value added. Equation (20) shows that the aggregate TFP growth rate is an expenditure share-weighted average of sectoral TFP growth rates. The correlation between $dTFP_i$ and $dTFP_c$ is equal to 0.31, pointing to a weak comovement between the two series and therefore suggesting that changes in aggregate TFP cannot be interpreted as a single homogeneous technological indicator.[21] It is precisely the sectoral structure that allows us to reconstruct a TFP series from the model consistent with the empirical counterpart in order to be able to conduct the comparison exercise in Section IIIA. Second, a two-sector model allows a more precise decomposition of the data variation into shocks, compared to a one-sector model.[22] Last, Görtz and Tsoukalas (2017) show that a two-sector model has a better fit with the data compared to a one-sector model.

B. *DSGE Estimation*

We estimate the DSGE model using quarterly US data for the period 1984:I–2017:I, the same sample period as for the VAR model.[23] We estimate the model using the following vector of observables: $[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta \log W_t, \pi_{C,t}, \Delta(P^I/P^C), \log L_t, R_t, R_t^S, \Delta \log S_t^h, \Delta \log N_t]$, which comprises output (Y_t), consumption (C_t), investment (I_t), real wage (W_t), consumption sector inflation $(\pi_{C,t})$, relative price of investment (P^I/P^C), hours worked (L_t), nominal interest rate (R_t), corporate bond spread (R_t^S), corporate equity (S_t^h), and bank equity, (N_t), respectively, and the term Δ denotes the first-difference operator. Variables

[21] In our sample average w_i is equal to 0.24. Therefore, by construction, the growth rate of the consumption-specific TFP holds a larger contribution to the growth rate of aggregate TFP. In addition, the aggregate TFP growth rate comoves more closely with the growth rate of consumption-specific TFP (correlation coefficient equal to 0.88) than the growth rate of investment-specific TFP (correlation coefficient equal to 0.72), further suggesting that movements in the growth rate of aggregate TFP are largely influenced by the growth rate in consumption-specific TFP.

[22] To illustrate, consider the relative price of investment (RPI) in the two-sector model, given as

$$\frac{P_{I,t}}{P_{C,t}} = \frac{\text{mark up}_{I,t}}{\text{mark up}_{C,t}} \frac{1 - a_c}{1 - a_i} \frac{A_t}{V_t} \left(\frac{K_{I,t}}{L_{I,t}}\right)^{-a_i} \left(\frac{K_{C,t}}{L_{C,t}}\right)^{a_c},$$

where a_c and a_i are capital shares in consumption and investment sector, respectively; V_t and A_t, are TFP in the investment and consumption sector, respectively; and $K_{x,t}/L_{x,t}, x = I, C$ is the capital-labor ratio in sector x. mark $\text{up}_{x,t}$ is the price markup, or inverse of the real marginal cost, in sector x. In one-sector models the investment specific technology, V, is identified one-for-one from the variation in the RPI alone. Moreover, in our sample the cyclical component of the RPI is procyclical rendering this restriction inappropriate, because investment-specific V shocks predict a countercyclical RPI response.

[23] Our focus on a Great Moderation period is detailed further in the online Appendix.

for aggregate quantities are expressed in real, per capita terms using civilian noninstitutional population. We demean the data prior to estimation.[24] We use these variables to keep the analysis as close as possible to related studies such as Smets and Wouters (2007); Justiniano, Primiceri, and Tambalotti (2010); and Khan and Tsoukalas (2012) while incorporating important financial variables. The online Appendix provides a detailed description of data sources. The financial variables consist of the corporate bond spread as provided (and updated) by Gilchrist and Zakrajšek (2012), a measure of market value of intermediaries' equity capital, and a measure of corporate equity for the nonfinancial corporate sector available from the Flow of Funds Accounts of the Federal Reserve Board (Z.1 Financial Accounts of the United States). The market value of commercial bank's equity we use is computed as the product of price and shares outstanding using monthly data from CRSP.

In the DSGE model, TFP news shocks compete with other shocks to account for the variation in the data. The cross-equation restrictions implied by the equilibrium conditions of the model identify the different shocks. We estimate a subset of parameters using Bayesian methods and calibrate the remaining parameters as described in online Appendix Table 7. The prior distributions conform to the assumptions in Justiniano, Primiceri, and Tambalotti (2010) and Khan and Tsoukalas (2012), as reported in Table 1 and posterior estimates of parameters common with these studies are broadly in line with them, so we do not discuss them in detail.[25]

We discuss the parameter estimates that control the degree of financial frictions, namely, the marginal adjustment costs parameters, κ^h and κ^B, which control the degree to which marginal costs are affected by the speed at which firms are adjusting equity and debt, and the limited enforcement parameter, λ_B. We set the prior means for these adjustment cost parameters equal to 0.1, broadly guided by marginal equity flotation costs and indirect distress costs associated with bond issuance estimated in Hennessy and Whited (2007). For the limited enforcement parameter, λ_B, we set a relative tight prior with a mean of 0.6, broadly consistent with the average (quarterly) GZ spread in the data of 0.5 percent and an average leverage ratio in our sample of 3.34.[26] Its interesting to comment on the posterior estimates for κ^h and κ^B. Information from the data implies posterior estimates which are shifted to the left of the prior means and are equal to 0.068 and 0.026 respectively. Note, that these estimates are still considerably different from zero (which would imply no rigidities) and imply quantitatively relevant rigidities in the adjustment of financial claims. Moreover, the estimates suggest that marginal equity adjustment costs are higher than corresponding marginal debt adjustment costs. The posterior estimate

[24] Removing sample means from the data prevents the possibility that counterfactual implications of the model for the low frequencies may distort inference on business cycle dynamics. For example, in the sample, consumption has grown by approximately 0.32 percent on average per quarter, while output has grown by 0.20 percent on average per quarter respectively. However, the model predicts that they grow at the same rate. Thus, if we hardwire a counterfactual common trend growth rate in the two series, we may distort inference on business cycle implications that is of interest to us.

[25] We have examined the identification of the model parameters using various metrics: evidence on prior and posterior densities, marginal likelihood comparisons between the baseline model and a model estimated without news shocks, and the tests of Iskrev (2010) and Koop, Pesaran, and Smith (2013). These results are available upon request.

[26] The leverage ratio, most consistent with the model concept, is computed as the ratio of commercial and industrial loans and securities in bank credit (numerator) to equity (denominator) for US commercial banks (H8 release).

Table 1—Prior and Posterior Distributions

		Prior distribution			Posterior distribution		
Parameter	Description	Distribution	Mean	SD	Mean	10%	90%
h	Consumption habit	Beta	0.50	0.10	0.9469	0.9334	0.9602
ν	Inverse labor supply elasticity	Gamma	2.00	0.75	1.3120	0.6438	2.0067
ξ_w	Wage Calvo probability	Beta	0.66	0.10	0.8905	0.8633	0.9161
ξ_C	C-sector price Calvo probability	Beta	0.66	0.10	0.9189	0.9019	0.9409
ξ_I	I-sector price Calvo probability	Beta	0.66	0.10	0.9008	0.8838	0.9182
ι_w	Wage indexation	Beta	0.50	0.15	0.1113	0.0348	0.1749
ι_{p_C}	C-sector price indexation	Beta	0.50	0.15	0.0469	0.0197	0.0784
ι_{p_I}	I-sector price indexation	Beta	0.50	0.15	0.8818	0.8250	0.9498
χ_I	I-sector utilization	Gamma	5.00	1.00	0.1131	0.1043	0.1211
χ_C	C-sector utilization	Gamma	5.00	1.00	0.0481	0.0453	0.0517
κ	Investment adj. cost	Gamma	4.00	1.00	4.0296	3.8929	4.1635
ϕ_π	Taylor rule inflation	Normal	1.90	0.10	1.8555	1.6623	1.9825
ρ_R	Taylor rule inertia	Beta	0.60	0.20	0.8925	0.8814	0.9079
ϕ_{dX}	Taylor rule output growth	Normal	0.125	0.10	0.5294	0.3237	0.6645
κ^h	Household financing adj. cost	Gamma	0.10	0.10	0.0679	0.0568	0.0783
κ^B	Bank financing adj. cost	Gamma	0.10	0.10	0.0263	0.0185	0.0315
λ_B	Fraction of funds bankers can divert	Beta	0.60	0.02	0.6235	0.5790	0.6597
Shocks: Persistence							
ρ_z	C-sector TFP growth	Beta	0.40	0.20	0.9529	0.9398	0.9668
ρ_v	I-sector TFP growth	Beta	0.40	0.20	0.8965	0.8661	0.9668
ρ_b	Preference	Beta	0.60	0.20	0.7450	0.6648	0.8269
ρ_μ	Marginal efficiency of investment	Beta	0.60	0.20	0.5553	0.4608	0.6700
ρ_g	Government spending	Beta	0.60	0.20	0.9721	0.9462	0.9966
$\rho_{\lambda_p^C}$	C-sector price markup	Beta	0.60	0.20	0.0261	0.0064	0.0393
$\rho_{\lambda_p^I}$	I-sector price markup	Beta	0.60	0.20	0.9785	0.9676	0.9914
ρ_{λ_w}	Wage markup	Beta	0.60	0.20	0.0847	0.0081	0.1511
ρ_{a_l}	C-sector stationary TFP	Beta	0.60	0.20	0.7267	0.4766	0.9958
ρ_{v_l}	I-sector stationary TFP	Beta	0.60	0.20	0.8785	0.8239	0.9406
ρ_{ς_C}	C-sector bank equity	Beta	0.60	0.20	0.1726	0.0431	0.2637
ρ_{ς_I}	I-sector bank equity	Beta	0.60	0.20	0.9722	0.9492	0.9962
Shocks: Standard Deviations							
σ_z	C-sector TFP	Inv Gamma	0.50	2*	0.0816	0.0396	0.1231
σ_z^4	C-sector TFP. 4Q ahead news	Inv Gamma	0.50	2*	0.1463	0.1171	0.1717
σ_z^8	C-sector TFP. 8Q ahead news	Inv Gamma	0.50	2*	0.1271	0.1018	0.1598
$\sigma_z^1 2$	C-sector TFP. 12Q ahead news	Inv Gamma	0.50	2*	0.1290	0.1051	0.1520
σ_v	I-sector TFP	Inv Gamma	0.50	2*	0.3045	0.2405	0.3786
σ_v^4	I-sector TFP. 4Q ahead news	Inv Gamma	0.50	2*	0.1668	0.1210	0.2148
σ_v^8	I-sector TFP. 8Q ahead news	Inv Gamma	0.50	2*	0.1636	0.1289	0.1985
$\sigma_v^1 2$	I-sector TFP. 12Q ahead news	Inv Gamma	0.50	2*	0.2112	0.1587	0.2567
σ_b	Preference	Inv Gamma	0.10	2*	36.4769	16.5068	53.2731
σ_μ	Marginal efficiency of investment	Inv Gamma	0.50	2*	4.6112	4.0549	5.1589
σ_g	Government spending	Inv Gamma	0.50	2*	0.4133	0.3774	0.4418
σ_{mp}	Monetary policy	Inv Gamma	0.10	2*	0.1068	0.0957	0.1173
$\sigma_{\lambda_p^C}$	C-sector price markup	Inv Gamma	0.10	2*	0.3707	0.3246	0.4187
$\sigma_{\lambda_p^I}$	I-sector price markup	Inv Gamma	0.10	2*	0.0257	0.0201	0.0301
σ_{λ_w}	Wage markup	Inv Gamma	0.10	2*	0.4138	0.3612	0.4797
σ_{a_l}	C-sector stationary TFP	Inv Gamma	0.50	2*	0.1930	0.1924	0.2568
σ_{v_l}	I-sector stationary TFP	Inv Gamma	0.50	2*	1.2480	1.1215	1.4034
σ_{ς_C}	C-sector bank equity	Inv Gamma	0.50	2*	15.7358	13.8086	17.1406
σ_{ς_I}	I-sector bank equity	Inv Gamma	0.50	2*	0.5878	0.2591	0.8717

Notes: The posterior distribution of parameters is evaluated numerically using the random walk Metropolis-Hastings algorithm. We simulate the posterior using a sample of 500,000 draws and discard the first 100,000 of the draws.

TABLE 2—VARIANCE DECOMPOSITION AT POSTERIOR ESTIMATES: BUSINESS CYCLE FREQUENCIES (6–32 QUARTERS)

	MEI	Bank equity shocks	All other shocks	Sum of TFP growth shock contribution: Unanticipated	All news	z news	v news
Output	7.6	0.2	20.1	19.8	52.3	47.3	5.1
Consumption	0.0	0.0	34.2	15.0	50.8	40.3	10.5
Investment	6.4	0.2	37.1	13.8	42.6	36.3	6.3
Total hours	4.9	0.1	34.8	10.0	50.1	46.3	3.8
Real wage	0.0	0.0	40.7	10.2	49.0	34.3	14.7
Nominal interest rate	4.5	0.1	56.4	3.0	36.0	34.3	1.7
C-sector inflation	0.0	0.0	95.4	0.6	4.0	1.1	2.9
GZ spread	12.0	7.8	38.4	4.5	37.3	33.7	3.6
Bank equity	0.3	69.9	2.6	3.9	23.4	23.3	0.0
Rel. price of investment	8.0	11.9	66.0	3.3	10.7	6.9	3.8
Corporate equity	0.0	0.0	65.7	13.3	21.1	6.6	14.5

Notes: MEI is the marginal efficiency of investment shock; bank equity shocks are the sum of the consumption sector and investment sector bank equity shock. Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage, the relative price of investment, bank equity, and corporate equity. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities. We report median shares.

for λ_B is equal to 0.62, and it implies a steady-state leverage ratio close to its counterpart in the data as discussed above.

C. *Results from the DSGE Model*

In this section we discuss key findings from the DSGE model on the empirical significance and the dynamic propagation of news shocks. We also provide a comparison with findings from standard models in the literature that abstract from financial frictions.

Table 2 reports the variance decomposition of the estimated DSGE model for each news shock and the sum of the unanticipated shocks. The entries show that the estimation assigns significant importance to TFP news shocks as a source of fluctuations. In their totality, TFP news shocks account for 52.3 percent, 50.8 percent, 42.6 percent, 50.1 percent of the variance in output, consumption, investment and hours worked, respectively, at business cycle frequencies. Consumption-specific news shocks play a major role in this total, accounting for 47.3 percent, 40.3 percent, 36.3 percent, 46.3 percent of the variance in the same macro aggregates. The estimation finds strong links between financial variables and real aggregates as sectoral news shocks explain a sizable share of the variance in the GZ spread (37.3 percent). These links help to quantify the amplification of TFP news shocks which, as discussed below, results from the presence of leveraged intermediaries.[27] TFP news

[27] The propagation of news shocks and the comovement of aggregate variables hinge on the countercyclical markups, as outlined in Görtz and Tsoukalas (2017) in the context of a two-sector model with nominal rigidities and news shocks. In the aftermath of a positive news shock, countercyclical markups move labor demand and supply curves rightwards offsetting the negative wealth effect on labor supply, thereby generating comovement in aggregate variables.

shocks are also quantitatively important for the variation in the nominal interest rate, real wage, and bank equity accounting for approximately 36 percent, 49 percent, and 23 percent of their variance, respectively. Bank equity shocks account for around 70 percent of the variance in the bank equity, but they are overall of very limited importance, especially for the key quantity macro aggregates. The online Appendix examines and verifies the robustness of our findings regarding the empirical significance of news shocks to two considerations. First, excluding observations from the Great Recession, addressing a misspecification concern regarding the policy rule due to a binding zero lower bound (ZLB) constraint. Second, introducing measurement wedges in the corporate bond spread in the mapping between model and data concepts, partly addressing a concern that default risk, which is absent from the model, may contribute to variation in credit spreads (though the VAR evidence of Section IC suggests the variation in credit spreads is not driven by default risk).

These findings are in sharp contrast to the results from a DSGE model that abstracts from financial frictions. To isolate the contribution of the financial channel in our model, we estimate a restricted version of the two-sector model that abstracts from financial frictions.[28] Table 3 compares the variance decomposition across the different models and shows that version of the model that abstracts from financial frictions finds a limited empirical role to news shocks. In this constrained version of the baseline model, the totality of TFP news shocks account for approximately 14 percent of the variation in output. This finding is consistent with related results in the DSGE literature that attribute a limited role to TFP news shocks (see, for example, Fujiwara, Hirose, and Shintani 2011; Khan and Tsoukalas 2012; and Schmitt-Grohé and Uribe 2012, among others). It is worth reporting that the estimated DSGE model can successfully replicate the significant predictive ability of the credit spread for economic activity consistent with the findings in Gilchrist and Zakrajšek (2012). The details of this forecasting exercise are described in the online Appendix.

We examine IRFs in order to gain intuition on the propagation of TFP news shocks and isolate the mechanism that enhances their empirical relevance in the baseline model with financial frictions. Figure 4 plots the response of selected variables to a three-year-ahead consumption-specific TFP news shock in the baseline model (solid line) together with those for the estimated two-sector model without financial frictions (dashed line). We normalize the shock to be of equal size across simulations.

From Figure 4 it is notable that the amplification of the news shock is significantly stronger in the model with the financial channel. In this model the impact of the consumption-specific news shock is amplified by the effect of corporate bond prices on intermediaries' equity. A positive news shock raises bond prices, which in turn boost bank equity. Better capitalized banks expand demand for capital assets, and the process further increases bond prices, leading to a strong investment boom and a decline in the excess premiums on holding bonds, noted as *C-Sector spread*

[28]This model turns off the financial channel, i.e., the balance sheet identity (15), the leverage constraint (16), the evolution of equity capital (17), and the financial constraint (9) that describe the financial sector as well as equations (7), (10), and (11) that allow capital services producers to raise funds from households. The only other difference is in the set of shocks. The restricted version has the same set of shocks except bank equity shocks which are specific to the baseline model.

TABLE 3—VARIANCE DECOMPOSITION: BUSINESS CYCLE FREQUENCIES (6–32 QUARTERS)

	Baseline model				Two-sector model w/o financial frictions			
	All TFP unanticipated	All TFP news	MEI	All other shocks	All TFP unanticipated	All TFP news	MEI	All other shocks
Output	19.8	52.3	7.6	20.3	4.0	14.4	52.3	29.3
Consumption	15.0	50.8	0.0	34.2	6.7	11.7	5.0	76.6
Investment	13.8	42.6	6.4	37.3	2.2	17.8	65.7	14.3
Total hours	10.0	50.1	4.9	35.0	4.8	18.5	47.1	29.6
Real wage	10.2	49.0	0.0	40.8	2.1	29.5	6.4	62.0
Nominal interest rate	3.0	36.0	4.5	56.5	1.1	9.0	37.7	52.2
C-sector inflation	0.6	4.0	0.0	95.4	6.0	2.8	1.2	89.9
GZ spread	4.5	37.3	12.0	46.2	N/A	N/A	N/A	N/A
Bank equity	3.9	23.4	0.3	72.5	N/A	N/A	N/A	N/A
Rel. price of investment	3.3	10.7	8.0	77.9	9.9	16.9	42.3	30.9
Corporate equity	13.3	21.1	0.0	65.7	N/A	N/A	N/A	N/A

Notes: Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage, the relative price of investment, bank equity, and corporate equity. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities. We report median shares.

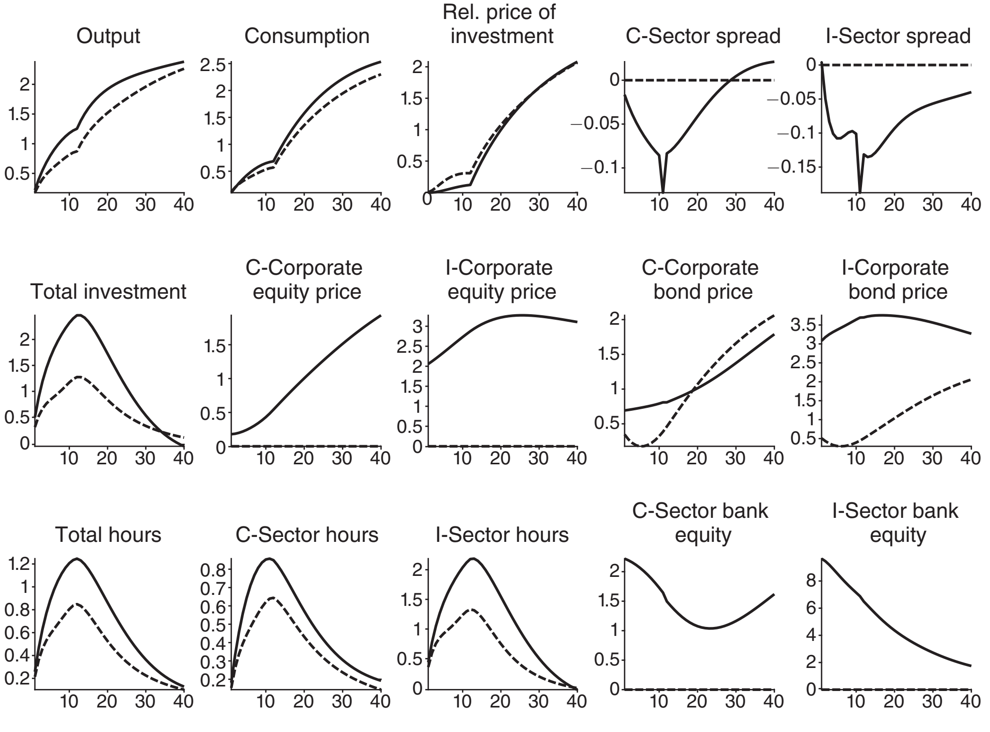

FIGURE 4. RESPONSES TO A 1 STANDARD DEVIATION TFP NEWS SHOCK (ANTICIPATED 12 QUARTERS AHEAD) IN THE CONSUMPTION SECTOR

Notes: Baseline model with financial intermediation (solid line), and estimated model without financial intermediation (dashed line) (baseline shock persistence and standard deviation). The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations.

and *I-Sector spread* in the figure. Although in equilibrium there is no default of intermediaries, higher equity implies that depositors are better protected from the costly enforcement/inefficient liquidation problem and hence they are willing to place deposits in banks that earn a lower excess premium. The response of the excess bond premium we have documented in Section IC is hence consistent with the narrative from the model. Figure 4 shows that the responses of bond prices are qualitatively different between the two models. In the baseline model with financial frictions, bond prices rise sharply due to the amplification effect of financial intermediaries on the demand for capital. As the stock of capital increases and accumulates, agents expect returns from capital to decline. Other things equal, the surge in bond prices creates a strong incentive to build new capital before the improvement in technology materializes, which in turn stimulates a strong rise in current hours worked and investment. In contrast, in the model without financial frictions, the shadow values (i.e., Tobin's q) of capital increase moderately on impact and rise further in the future, which suppresses—relative to the baseline—current investment spending in anticipation of future increase in the returns to capital.[29] It is also noteworthy to report that both bond prices and corporate equity prices in the model rise strongly in response to the news shock (see middle row in the figure) consistent with the VAR evidence.

Our study provides relevant insights on the significance of the marginal efficiency of investment (MEI) shock, which recent studies that estimate DSGE models with and without news shocks (Khan and Tsoukalas 2012 and Justiniano, Primiceri, and Tambalotti 2010, respectively), find considerably more important than TFP shocks to explain business cycles fluctuations.[30] We corroborate these findings in the estimated version of the model that abstracts from the financial channel (see Table 3). For instance, in the two-sector model without financial frictions, MEI shocks explain the bulk of movements in the variance of output (52 percent), investment (66 percent), and hours worked (47 percent). In contrast, in the baseline model with the financial sector, MEI shocks account for approximately, 8 percent, 6 percent, and 5 percent in the variance of the same set of macroeconomic aggregates.[31] The key reason for the reduced role of MEI shocks in the presence of financial frictions is related to the fact that an exogenous increase in MEI generates a fall in the price of installed capital by increasing the transformation rate of investment goods to installed capital. The decline in capital prices severs the financial channel that stimulates equity capital gains for the financial intermediaries in response to an increase in investment demand and capital prices. Thus, a decline in capital prices induces a fall in bank equity and restricts the facilitation of lending and investment spending.

[29] Strictly speaking, the comparison in the figure is between the shadow value of capital in the model without the financial channel to the bond price, which represents the price of a claim to capital, in the baseline model.

[30] We include the MEI shock in the estimation for comparison purposes with the literature. The MEI shock differs from the investment-specific shock in that the latter is a permanent shock and affects only the productivity of the investment sector. By contrast, the MEI impacts the transformation of investment goods to installed capital and affects both sectors.

[31] We show in the online Appendix that the results of the comparison between the baseline model and a two-sector model without financial frictions also extend to a one-sector model without the financial channel. In comparison to the baseline setup the role of news shocks is much more limited in the one-sector model and MEI shocks are more relevant for explaining variations in macroeconomic aggregates.

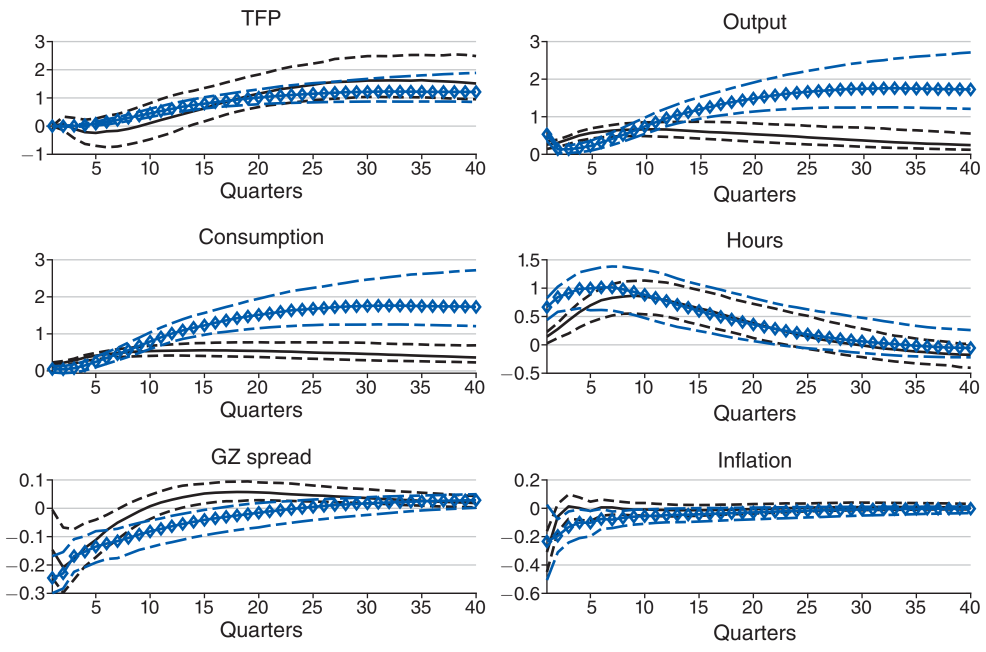

Figure 5. TFP News Shock

Notes: The solid black line is the impulse response to TFP news shock from a six-variable VAR featuring aggregate TFP, corporate bond spread (GZ spread), consumption, output, hours, CPI inflation, estimated with 5 lags. The blue line with diamonds is the median impulse response to an aggregate TFP news shock estimated from a VAR on 300 samples, generated from the model. The black dashed (blue dot-dashed) lines are the corresponding 16 percent and 84 percent confidence bands. Units of the vertical axes are percentage deviations.

The same logic operates in the case of investment-specific shocks of the unanticipated or anticipated type.

III. Reconciling DSGE and VAR Results

A. *The DSGE as the Data Generating Process*

In this section we compare the dynamics responses to TFP news shocks across the DSGE and VAR analysis. We perform a Monte Carlo experiment and generate 300 samples of artificial data from the DSGE model, drawing parameter values from the posterior distribution. We compare the empirical IRF from the VAR model against those estimated with identical VAR specifications (along with posterior bands) on the artificial data samples. This exercise is similar in spirit to Barsky, Basu, and Lee (2015), who compare empirical VAR and model implied VAR responses produced by a standard calibrated New Keynesian model. Following the methodology in Fernald (2014), we extract a model-based aggregate TFP measure by weighting (using GDP shares) together the two model-based sectoral TFP growth components as in equation (20), referred to in Section II.

Figure 5 compares the IRF from the empirical VAR model (black lines) with those from the Monte Carlo experiment (blue lines). Several features are noteworthy. First, the model-based VAR responses exhibit the delayed response of TFP along with an immediate strong and significant increase in the activity variables that is also present in the empirical VAR responses. Second, we also observe an immediate and significant decline in the credit spread in the model-based VAR responses consistent with the empirical VAR responses. Overall, the empirical and model-implied responses are qualitatively consistent, indicating a broad-based expansion ahead of the future increase in TFP. Finally, we turn to discuss the response of inflation. As the reader can observe, at least qualitatively, the model-implied responses also produce an immediate (median) decline in inflation as in the empirical VAR responses. Moreover, the model-implied VAR response predicts an inflation response path, where the initial, compared to the empirical VAR response, decline is smaller and it is not significantly different from zero (as is the entire path in the model-implied responses). Therefore, the model, statistically speaking, does not deliver a strong and robust decline in inflation as in the data. In the model, which is built around a New Keynesian core, current inflation is a function of future real marginal costs and the latter decline when higher TFP materializes. But the impact response of inflation depends on the entire path of real marginal costs. We know from Figure 4 that a TFP news shock generates an immediate and strong boom in activity and this comes hand in hand with an increase in real marginal costs in the short term, before any future realization of TFP raises productivity. Thus, inflation can increase or decrease on impact depending on whether the short-term increase of real marginal cost due to the initial outburst of activity in anticipation of the future increase in productivity outstrips or falls short of the medium- to long-term decline in real marginal cost after productivity has improved. In other words, the anticipation horizon matters. The model contains one-, two-, and three-year-ahead future TFP growth shocks. Figure 6 shows the responses of inflation and marginal costs to these shocks. Future real marginal costs decline very sharply and outstrip the initial short-term increase in response to the one-year-ahead future TFP shock, and inflation declines. A longer horizon of anticipation in the future TFP increase however, produces the opposite inflation dynamic, i.e., an increase on impact, because the short-term rise in real marginal cost counterbalances the fall in real marginal costs when productivity improves. Among the key parameters of the model which play a role in how real marginal costs respond and ultimately determine the response of inflation are the degree of wage rigidities, the parameters of the policy rule, and the parameters that govern the process for TFP. The new finding from this analysis is the dependence of the short-term inflation response on the timing of the news shock, i.e., the anticipation horizon for the future rise in TFP. At the estimated parameters of the model, as shown in Figure 6, inflation falls on impact for the one-year-ahead shock and rises for the longer anticipated news shocks.

Qualitatively, the similarity of the dynamic VAR responses in Figure 5 is a success of the model considering there are key differences in the estimation methodologies between the DSGE and VAR methods. The two methods identify the news shock from different empirical moments, they use a different set of observables and consequently entertain a different number of shocks. The qualitative similarity of

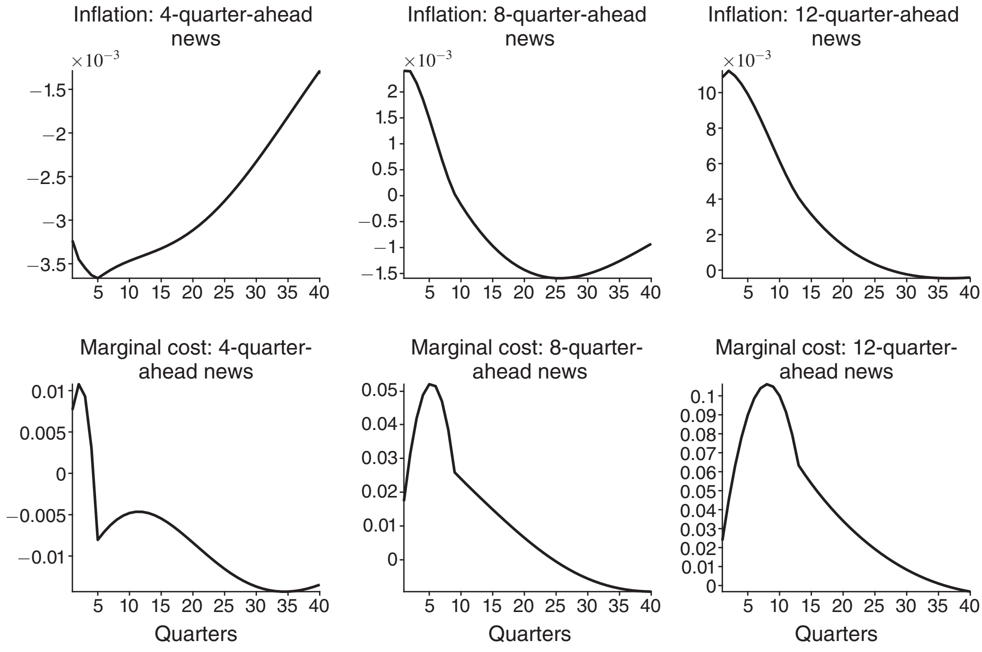

Figure 6. DSGE Responses to TFP News Shocks

Note: Impulse responses of inflation and real marginal cost to a 4-quarter-ahead (left column), 8-quarter-ahead (middle column) and 12-quarter-ahead (right column) TFP news shock.

responses suggests that accounting for financial frictions can go some way to reconcile existing and often conflicting results in the literature using the DSGE and VAR methodologies. In the following section, we undertake a variance decomposition exercise to suggest that using this metric there is also a good degree of quantitative similarity in the role the two methodologies assign to TFP news shocks.

B. *A Quantitative Evaluation*

To evaluate the quantitative differences between the VAR and DSGE methods, we compare the forecast error variance decompositions (FEVD) for the totality of TFP news shocks obtained from the VAR and DSGE models at business cycle frequencies (6–32 quarters). Table 4 shows the FEVD of the common variables in the VAR model (panel A), the baseline DSGE model with financial frictions (panel B), and the DSGE model without financial frictions (panel C).

Table 4 shows that in general the median shares of the FEVD accounted for by TFP news shocks in the DSGE model with financial frictions are close and, in the vast majority of cases, fall within the posterior bands of the median shares predicted by the VAR model. The model that abstracts from financial frictions predicts instead a considerably smaller role that news shocks play in explaining movements in macroeconomic variables. An obvious shortcoming of the model without financial

Table 4—Share of Variance Explained by TFP News Shocks

	Horizon (quarters)				
	6	12	20	24	32
Panel A. VAR (medians and 16% and 84% posterior bands in brackets)					
Output*	44	55	64	67	69
	[12 66]	[19 76]	[29 83]	[33 84]	[37 86]
Consumption*	48	60	69	72	75
	[16 69]	[28 79]	[38 84]	[42 87]	[48 89]
Investment ‡	32	47	60	63	67
	[8 60]	[16 70]	[32 79]	[37 81]	[41 85]
Total hours*	36	46	49	47	45
	[7 63]	[11 72]	[13 74]	[14 72]	[14 69]
GZ spread*	34	34	34	35	38
	[10 58]	[11 56]	[13 56]	[13 57]	[15 58]
Excess bond premium♭	39	37	38	38	39
	[13 63]	[14 60]	[15 58]	[16 58]	[17 59]
Bank equity†	86	88	88	88	86
	[76 92]	[79 93]	[77 93]	[73 93]	[68 93]
S&P 500*	62	69	71	70	68
	[35 80]	[44 84]	[46 85]	[46 85]	[45 84]
C-sector inflation*	21	21	21	22	22
	[9 38]	[11 38]	[11 37]	[12 37]	[12 37]
Panel B. DSGE model with financial frictions (medians)					
Output	33	44	44	46	51
Consumption	32	38	32	36	49
Investment	35	41	39	36	35
Hours	33	44	46	44	42
C-sector inflation	0	1	3	5	8
GZ spread	48	29	31	33	40
Bank equity	24	23	24	24	25
Corporate equity	30	26	17	16	16
C-sector price of capital	19	24	35	40	45
I-sector price of capital	74	74	74	73	71
Average price of capital	47	49	55	57	58
Panel C. DSGE model without financial frictions (medians)					
Output	9	8	9	12	19
Consumption	25	22	9	8	12
Investment	4	5	12	15	20
Hours	7	10	14	17	22
C-sector inflation	0	1	3	4	6
C-sector price of capital	11	15	18	18	16
I-sector price of capital	19	22	31	33	32
Average price of capital	15	19	25	26	24

Notes: The FEV of variables denoted with * are obtained from a seven-variable VAR baseline specification with TFP, consumption, output, hours, GZ spread, S&P500 and inflation (consistent with VAR in Figure 1). The FEV of variables denoted with ♭ are obtained from the baseline VAR specification in which the GZ spread is replaced with the EBP. The FEV of variables denoted with † are obtained from the baseline VAR specification, where the EBP and bank equity replace the GZ spread and the S&P500. The FEV of variables denoted with ‡ are obtained from the baseline VAR specification where investment replace consumption.

frictions, relative to the baseline model, is its inability to account for the variance in the corporate bond spread indicator. We see this exercise as a useful and informative test to show that accounting for financial frictions, two important methodologies—VAR and DSGE—independently provide a consistent reading on the

Table 5—Variance Decomposition: Business Cycle Frequencies (6–32 Quarters)

	TFP news baseline model	TFP news simple model	Financial shocks simple model
Output	52.3	69.7	9.3
Consumption	50.8	65.9	9.7
Total investment	42.6	74.6	16.0
Total hours	50.1	80.2	11.4
GZ spread	37.3	13.7	66.6

Notes: Decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, and investment. The spectral density is computed from the model's state space representation with 500 bins for frequencies covering the range of periodicities. We report median shares.

importance of TFP news shocks. This is despite the differences in the two methods as discussed in the previous section.

C. *TFP News and Financial Shocks*

In this section, we report results from a streamlined version of the baseline model that encompasses a richer menu of financial shocks. It introduces, in addition to bank equity shocks, shocks that perturb the excess return to capital, equation (18). These shocks can be interpreted as "risk appetite" shocks: ceteris paribus, a positive shock of this type increases the demand for assets by financial intermediaries, and consequently the supply of credit.[32] Our goal is to focus on a relative quantitative comparison between disturbances that emanate in the real economy and disturbances that emanate in the financial sector. For this purpose we economize on disturbances that do not admit a straightforward structural interpretation or have very limited contribution in accounting for the variance in the data.[33] We estimate this version of the model, and show the variance decomposition in Table 5—the full decomposition is reported in the online Appendix. There are two findings to report.[34] First, the empirical significance of TFP news continues to be substantial, similar to the baseline model. Second, "risk appetite" shocks explain a sizable fraction of fluctuations, accounting for 9.3 percent, 9.7 percent, 16.0 percent, 11.4 percent of the variance in output, consumption, investment, and hours respectively, and 66.6 percent of variance in the GZ spread.[35] This is consistent with the notion that

[32] We remain agnostic on the timing of arrival of "risk appetite" shocks and incorporate news components—as well as an unanticipated component—consistent with the work of Christiano, Motto, and Rostagno (2014) who emphasized the importance of financial risk news shocks.

[33] To this end we have removed the preference, MEI, government spending, stationary sectoral TFP, and markup shocks in the investment sector. Details are provided in the online Appendix.

[34] In the online Appendix we also report results from estimation of the baseline model with risk appetite shocks. As in the streamlined version, in the extended version the empirical significance of TFP news is substantial and similar to the baseline.

[35] Its interesting to note that quantitatively the role assigned by the model to financial shocks is broadly consistent with the VAR decomposition results for activity aggregates and EBP component of the GZ spread reported in Gilchrist and Zakrajšek (2012).

risk shocks, independently from real disturbances, affecting the supply of credit can have significant real effects.

IV. Conclusion

This paper examines the empirical significance and dynamic effects of TFP news shocks in the context of financial frictions using complementary VAR and DSGE methods. The VAR model identifies two robust stylized facts. *First*, a shock to future TFP is associated with a significant decline of credit spread indicators, with highly predictive content as recently emphasized by Gilchrist and Zakrajšek (2012) along with a broad-based expansion in activity. The credit spread indicators include the GZ spread and the excess bond premium. The decline in credit spread indicators is associated with an improvement in the balance sheet conditions of financial intermediaries, suggesting that credit supply conditions are critical for the propagation of news shocks. *Second*, we independently identify a single shock that seeks to explain as much as possible of the unforecastable movements in the excess bond premium. This single shock explains approximately 75 percent in the forecast error variance of the latter. Importantly, the dynamic macro effects generated by this shock are qualitatively and quantitatively very similar to the macro effects generated by the TFP news shock. This finding provides strong support for the notion that movements in credit spread indicators are tightly linked with news shocks.

We employ a DSGE model with financial frictions and suggest it is a useful structural framework to understand the propagation of news shocks emphasizing credit supply frictions. The model analysis shows that the critical mechanism for the strong macro effects of news shocks relies on the linkages between leveraged equity, bond prices, and excess premiums which vary inversely with the balance sheet condition of intermediaries, consistent with the VAR evidence. Moreover, the estimated model generates dynamic responses and quantitative estimates of TFP news shocks very similar to those obtained from the VAR model. The consistent assessment of news shocks across methods provides support for the traditional "news view" of business cycles.

Our analysis suggests several avenues for future research that go beyond the scope of this paper. Our model features an exogenous TFP process where agents receive signals about future TFP developments. Whereas this is a parsimonious and flexible way to introduce "news" shocks in a medium-scale DSGE, it nevertheless is silent about the drivers of TFP dynamics. We believe that endogenous medium-term developments in TFP may interact with short-term financing frictions in ways that have not been emphasized in the literature, and such interactions may be important to understand why some technologies are successfully adopted while others never make it to the technology frontier. One possible avenue to unify the traditional notion of TFP news with endogenous TFP is to introduce imperfect learning (noisy signals) about the profitability of new innovations. In such an environment noisy signals will give rise to forecast errors about future profitability and eventually productivity (as a fraction of innovations are adopted) and has the ability to generate cycles due to expectation shifts (Pigou cycles) as emphasized in the traditional news literature within an endogenous TFP framework. Moreover, introducing constrained banks to fund innovation activity as in Queralto (2020) has the potential to amplify forecast errors due to noise. These features combined have two potentially interesting implications. First, the emergence of wasteful financing booms which are eventually reversed when the impact of noise dies out, boom-bust patterns in the spirit of Pigou cycles. Second, how and to what extent high frequency noise interacts with medium-term TFP dynamics. Of course, the challenge remains of how such a model will better account for the S-shaped delayed pattern for TFP documented in this paper. We leave a detailed exploration of such considerations for future work.

REFERENCES

Altinkiliç, Oya, and Robert S. Hansen. 2000. "Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs." *Review of Financial Studies* 13 (1): 191–218.

Barsky, Robert B., Susanto Basu, and Keyoung Lee. 2015. "Whither News Shocks?" In *NBER Macroeconomics Annual 2014*, edited by Jonathan A. Parker and Michael Woodford, 225–64. Chicago: University of Chicago Press.

Barsky, Robert B., and Eric R. Sims. 2011. "News Shocks and Business Cycles." *Journal of Monetary Economics* 58 (3): 273–89.

Basu, Susanto, John Fernald, Jonas Fisher, and Miles Kimball. 2013. "Sector Specific Technical Change." Unpublished.

Basu, Susanto, John G. Fernald, and Miles S. Kimball. 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96 (5): 1418–48.

Beaudry, Paul, and Bernd Lucke. 2010. "Letting Different Views about Business Cycles Compete." In *NBER Macroeconomics Annual 2009*, edited by Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, 413–55. Chicago: University of Chicago Press.

Beaudry, Paul, Deokwoo Nam, and Jian Wang. 2012. "Do Mood Swings Drive Business Cycles and Is It Rational?" Unpublished.

Beaudry, Paul, and Franck Portier. 2004. "An Exploration into Pigou's Theory of Cycles." *Journal of Monetary Economics* 51 (6): 1183–1216.

Beaudry, Paul, and Franck Portier. 2006. "Stock Prices, News, and Economic Fluctuations." *American Economic Review* 96 (4): 1293–1307.

Beaudry, Paul, and Franck Portier. 2014. "News-Driven Business Cycles: Insights and Challenges." *Journal of Economic Literature* 52 (4): 993–1074.

Ben Zeev, Nadav, and Hashmat Khan. 2015. "Investment-Specific News Shocks and U.S. Business Cycles." *Journal of Money, Credit and Banking* 47 (7): 1443–64.

Boldrin, Michele, Lawrence J. Christiano, and Jonas D. M. Fisher. 2001. "Habit Persistence, Asset Returns, and the Business Cycle." *American Economic Review* 91 (1): 149–66.

Calvo, Guillermo A. 1983. "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics* 12 (3): 383–98.

Cascaldi-Garcia, Danilo. 2019. "Dynamic Effects of News Shocks under Uncertainty." Unpublished.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy* 113 (1): 1–45.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review* 104 (1): 27–65.

Cooley, Thomas F., and Vincenzo Quadrini. 2001. "Financial Markets and Firm Dynamics." *American Economic Review* 91 (5): 1286–1310.

Covas, Francisco, and Wouter J. Den Haan. 2011. "The Cyclical Behavior of Debt and Equity Finance." *American Economic Review* 101 (2): 877–99.

Erceg, Christopher J., Dale W. Henderson, and Andrew T. Levin. 2000. "Optimal Monetary Policy with Staggered Wage and Price Contracts." *Journal of Monetary Economics* 46 (2): 281–313.

Favara, Giovanni, Simon Gilchrist, Kurt F. Lewis, and Egon Zakrajšek. 2016. "Updating the Recession Risk and the Excess Bond Premium." FEDS Notes, the Board of Governors of the Federal Reserve System.

Federal Reserve Bank of St. Louis. 2017. FRED. Various dates. https://fred.stlouisfed.org (accessed September 2017).

Fernald, John. 2014. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." Federal Reserve Bank of San Francisco Working Paper 2012-19.
Forni, Mario, Luca Gambetti, and Luca Sala. 2014. "No News in Business Cycles." *Economic Journal* 124 (581): 1168–91.
Francis, Neville, Michael T. Owyang, Jennifer E. Roush, and Riccardo DiCecio. 2014. "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks." *Review of Economics and Statistics* 96 (4): 638–47.
Fujiwara, Ippei, Yasuo Hirose, and Mototsugu Shintani. 2011. "Can News Be a Major Source of Aggregate Fluctuations? A Bayesian DSGE Approach." *Journal of Money, Credit and Banking* 43 (1): 1–29.
Galí, Jordi, and Luca Gambetti. 2009. "On the Sources of the Great Moderation." *American Economic Journal: Macroeconomics* 1 (1): 26–57.
Gerali, Andrea, Stefano Neri, Luca Sessa, and Federico M. Signoretti. 2010. "Credit and Banking in a DSGE Model of the Euro Area." *Journal of Money, Credit and Banking* 42 (S1): S107–41.
Gertler, Mark, and Peter Karadi. 2011. "A Model of Unconventional Monetary Policy." *Journal of Monetary Economics* 58 (1): 17–34.
Gertler, Mark, and Nobuhiro Kiyotaki. 2010. "Financial Intermediation and Credit Policy in Business Cycle Analysis." In *Handbook of Monetary Economics*, Vol. 3, edited by Benjamin M. Friedman and Michael Woodford, 547–99. Amsterdam: Elsevier.
Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720.
Gomes, Joao F. 2001. "Financing Investment." *American Economic Review* 91 (5): 1263–85.
Görtz, Christoph, Christopher Gunn, and Thomas A. Lubik. 2022. "Is There News in Inventories?" *Journal of Monetary Economics* 126: 87–104.
Görtz, Christoph, and John D. Tsoukalas. 2017. "News and Financial Intermediation in Aggregate Fluctuations." *Review of Economics and Statistics* 99 (3): 514–30.
Görtz, Christoph, John D. Tsoukalas, and Francesco Zanetti. 2022. "Replication data for: News Shocks under Financial Frictions." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.38886/E130141V1.
Hennessy, Christopher A., and Toni M. Whited. 2007. "How Costly Is External Financing? Evidence from a Structural Estimation." *Journal of Finance* 62 (4): 1705–45.
Huffman, Gregory W., and Mark A. Wynne. 1999. "The Role of Intratemporal Adjustment Costs in a Multisector Economy." *Journal of Monetary Economics* 43 (2): 317–50.
Ireland, Peter N., and Scott Schuh. 2008. "Productivity and US Macroeconomic Performance: Interpreting the Past and Predicting the Future with a Two-Sector Real Business Cycle Model." *Review of Economic Dynamics* 11 (3): 473–92.
Iskrev, Nikolay. 2010. "Local Identification in DSGE Models." *Journal of Monetary Economics* 57 (2): 189–202.
Jaimovich, Nir, and Sergio Rebelo. 2009. "Can News about the Future Drive the Business Cycle?" *American Economic Review* 99 (4): 1097–1118.
Jermann, Urban, and Vincenzo Quadrini. 2009. "Financial Innovations and Macroeconomic Volatility." Unpublished.
Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic Effects of Financial Shocks." *American Economic Review* 102 (1): 238–71.
Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti. 2010. "Investment Shocks and Business Cycles." *Journal of Monetary Economics* 57 (2): 132–45.
Khan, Hashmat, and John Tsoukalas. 2012. "The Quantitative Importance of News Shocks in Estimated DSGE Models." *Journal of Money, Credit and Banking* 44 (8): 1535–61.
Koop, Gary, M. Hashem Pesaran, and Ron P. Smith. 2013. "On Identification of Bayesian DSGE Models." *Journal of Business and Economic Statistics* 31 (3): 300–14.
Leary, Mark T., and Roni Michaely. 2011. "Determinants of Dividend Smoothing: Empirical Evidence." *Review of Financial Studies* 24 (10): 3197–3249.
Leary, Mark T., and Michael R. Roberts. 2005. "Do Firms Rebalance Their Capital Structures?" *Journal of Finance* 60 (6): 2575–2619.
Moran, Patrick, and Albert Queralto. 2018. "Innovation, Productivity, and Monetary Policy." *Journal of Monetary Economics* 93: 24–41.
Papanikolaou, Dimitris. 2011. "Investment Shocks and Asset Prices." *Journal of Political Economy* 119 (4): 639–85.
Philippon, Thomas. 2009. "The Bond Market's *q*." *Quarterly Journal of Economics* 124 (3): 1011–56.

Queralto, Albert. 2020. "A Model of Slow Recoveries from Financial Crises." *Journal of Monetary Economics* 114: 1–25.

Ramey, Valerie A., and Matthew D. Shapiro. 2001. "Displaced Capital: A Study of Aerospace Plant Closings." *Journal of Political Economy* 109 (5): 958–92.

Schmitt-Grohé, Stephanie, and Martín Uribe. 2012. "What's News in Business Cycles." *Econometrica* 80 (6): 2733–64.

Shiller, Robert. 2017. US Stock Markets 1871–Present and CAPE Ratio. http://www.econ.yale.edu/~shiller/data.htm (accessed September 2017).

Smets, Frank, and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review* 97 (3): 586–606.

Uhlig, Harald. 2003. "What Moves Real GNP?" Unpublished.

Wharton Research Data Services. 2018. CRSP Database, 1984–2017. https://wrds-www.wharton.upenn.edu/ (accessed March 2018).