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R&D Shocks and News Shocks

Most of the theoretical work in the news shock literature abstracts away from structural explanations, assuming instead that news is a pure signal giving agents advance notice that aggregate technology will undergo exogenous change at some future point. This paper proposes that a surprise improvement in sector-specific productivity in the research and development sector can be seen as news about aggregate productivity. I not only offer a deeper explanation for the news but also show that the model performs modestly better in matching empirical facts than a standard, one-sector neoclassical growth model augmented with exogenous news shocks does.

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THE EXPECTATION-DRIVEN business cycle hypothesis postulates that news about the future can be an important source of business cycle fluctuations. This theory was originally advanced by Pigou (1927) and was resurrected by Beaudry and Portier (2006) in a modern, empirical form that attracted renewed interest from contemporary economists. However, it is difficult to apply this hypothesis to the standard dynamic stochastic general equilibrium (DSGE) model because the model predicts that the wealth effect of good news causes households to seek additional consumption of both goods and leisure; hence, contrary to the hypothesis, the model predicts that production will slow on the arrival of good news. A large body of literature has subsequently been developed that seeks mechanisms through which the model can generate the appropriate comovement, that is,

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an economic boom defined as simultaneous expansion in output, consumption, investment, and hours worked. A short list of the relevant studies includes Beaudry and Portier (2004), who propose a multisector model with complementarity between services and infrastructure; Den Haan and Kaltenbrunner (2009), who present a matching framework with equilibrium underinvestment; and Jaimovich and Rebelo (2009), who introduce a class of preferences that weaken the wealth effect on labor supply.[1]

Conversely, a recent empirical study suggests that the literature's focus on impact effects may have been somewhat misplaced. This point was made by Barsky and Sims (2011), who develop a novel method for identifying news shocks through the application of principal components. Their method is arguably an improvement over other approaches because it relies solely upon a weak assumption that a limited number of shocks leads to movements in aggregate technology, whereas other approaches rely upon auxiliary assumptions about other shocks or on the persistence of variables. Applying the technique to vector autoregression (VAR) models estimated with U.S. data leads to surprising results, namely, that favorable news about future total factor productivity (TFP) is, on impact, associated with an increase in consumption and decreases in output, investment, and hours. These results are consistent with the predictions of a wide class of existing DSGE models, including the most basic neoclassical models.[2] Because Barsky and Sims also find that the identified news shocks explain an important share of output variance at medium frequencies, the authors argue that the literature should move away from fixing impact comovements and toward deeper structural explanations for news.

The current paper proposes such an explanation. Specifically, I argue that what Barsky and Sims (2011) identify as a news shock in their VAR model is a surprise improvement in sector-specific productivity in the research and development (R&D) sector. I support this argument by constructing and evaluating an otherwise standard two-sector neoclassical growth model, with sector-specific productivity shocks. I also construct a standard, one-sector neoclassical growth model in which a news shock is modeled as a pure signal, giving agents advance notice that aggregate technology will undergo an exogenous change at some future point. Notice that these shocks are fundamentally different, as the former is a real shock, having contemporaneous effects on sector-specific productivity, while the latter is a signal, having no effects on current fundamentals. Because the two models have different policy implications, having the correct model is important for selecting the optimal policy.[3] I show that the

1. Schmitt-Grohe and Uribe (2012) and Fujiwara, Hirose, and Shintani (2011) perform structural Bayesian estimations of the importance of anticipated shocks.

2. See also Nam and Wang (2010), who apply Barsky and Sims's (2011) identification technique to analyze exchange rate dynamics.

3. The two-sector model implies that the government can improve welfare by giving production subsidies for monopolistic producers. In contrast, there is no role for the government in improving welfare in the one-sector model, as the allocation in the model is always efficient.

two-sector model is slightly more in line with the empirical facts than the one-sector model.[4]

In my model economy, R&D is pursued for product development. Specifically, I introduce product entry subject to sunk product development costs as in Bilbiie, Ghironi, and Melitz (2012). These authors stress the consumer love for variety; however, based on an alternative interpretation that entry and exit take place in the intermediate goods sector as in variety-based endogenous growth models (see, e.g., Romer 1990, Grossman and Helpman 1991, Aghion and Howitt 1997), product development can be interpreted as a productivity-enhancing activity.

However, I make two modifications to Bilbiie, Ghironi, and Melitz (2012), each of which I demonstrate is important in accounting for the empirical findings of Barsky and Sims (2011). First, I introduce a simple product cycle; that is, a product is initially monopolistically produced and later, competitively produced. Futagami and Iwaisako (2007) introduce such a structure to analyze the effects of patent length on social welfare; however, because I take a broad view that the source of monopoly incorporates not only the formal patent system but also informal protections surrounding trade secrets and brand image, I call products in the first stage of the product cycle "innovative products" and products in the second stage of the product cycle "maturing products." I also assume that the transition from an innovative product to a maturing product takes place stochastically.

Second, I introduce knowledge spillover. Specifically, I assume that a larger stock of innovative products improves product innovation efficiency and, more importantly, that this knowledge spillover is not an externality but is internalized by agents performing R&D. In the endogenous growth literature, this type of knowledge spillover is introduced to analyze the role of private knowledge accumulation for in-house R&D (see, e.g., Smulders and van de Klundert 1995, Peretto 1996, 1998). However, my specification is closer to McGrattan and Prescott (2010), in which intangible capital is simultaneously useful in both goods-producing sectors and intangible capital-producing sectors. In particular, the product innovation function in my model economy is constant returns to scale, as is the production function of intangible capital in McGrattan and Prescott's model. This assumption greatly simplifies the analysis because it allows the introduction of an aggregate product innovation function to the model economy.[5]

I find that Barsky and Sims's (2011) decomposition correctly identifies a news shock when it is applied to data artificially generated by the one-sector model, but interestingly, the same decomposition identifies and labels a sector-specific productivity

4. The current paper only considers news shocks whose signal materializes with probability one. However, the literature also studies other types of news shocks, most notably those that accommodate revisions in expectations, such as anticipated increases in productivity that fail to materialize (e.g., Beaudry and Portier 2004). It is a limitation of this study that the two-sector model presented in this paper is not well equipped to discuss them.

5. This is an important difference from the aforementioned prominent contributions in the endogenous growth literature; that is, adopting a particular knowledge creation function, Smulders and van de Klundert (1995) and Peretto (1996, 1998) analyze how detailed market structure, such as the number and size distribution of firms, affects the aggregate economy.

shock as news when it is applied to the data artificially generated by the two-sector model. Nonetheless, both models are largely consistent with the empirical evidence, in the sense that the estimated impulse response functions of TFP, consumption, output, investment, and hours are largely in line with their empirical counterparts. I also show that the two-sector model performs modestly better than the one-sector model in that it is able to predict a qualitatively reasonable impact response of the stock market value and is slightly better able to account for the empirical patterns of forecast error variance decompositions. I also demonstrate that the model economies presented in this paper cannot account for the empirical findings in Beaudry and Portier (2006).

1. MODEL ECONOMIES

1.1 One-Sector Model

The one-sector model consists of the representative household, the representative firm, and the government. The same model is adopted by Barsky and Sims (2011) for demonstrating that this simple model performs relatively well in matching their empirical findings. The household maximizes the expected lifetime utility value, defined as:

$$E_0\left[\sum_{t=0}^{\infty}\beta^t\left(\log\left(C_t-bC_{t-1}\right)-\psi_t\frac{H_t^{1+1/\eta}}{1+1/\eta}\right)\right]$$

subject to the flow budget constraint and the capital accumulation rule,

$$C_t+I_t=(1-\tau_t)\left(W_tH_t+R_tK_t\right)$$

$$K_{t+1}=\left(1-\delta^K\right)K_t+I_t.$$

Variable definitions are standard. The income tax τ_t is set by the government. Preference shock ψ_t follows a stationary process,

$$\log\psi_t=\rho_\psi\log\psi_{t-1}+u_{\psi t}.$$

The competitive, representative firm operates production technology,

$$Y_t=(TFP_t)\,K_t^\alpha H_t^{1-\alpha}.$$

The level of TFP is exogenous, and I follow Section 4 of Barsky and Sims (2011) in specifying its dynamic property; that is, TFP is decomposed into two parts:

$$\log TFP_t=\log A_t+\log Z_t,$$

TABLE 1
ONE-SECTOR MODEL SUMMARY

Production	$Y_t = (TFP_t)\, K_t^{\alpha} H_t^{1-\alpha}$
TFP	$TFP_t = A_t Z_t$
Consumption	$\frac{1}{C_t - bC_{t-1}} - \lambda_t + E_t\left[\beta\left(\frac{-b}{C_{t+1} - bC_t}\right)\right] = 0$
Hours	$\lambda_t (1 - g_t)\, \frac{(1-\alpha)Y_t}{H_t} = \psi_t H_t^{\frac{1}{\eta}}$
Euler equation	$\lambda_t = E_t\left[\beta\lambda_{t+1}\left((1 - g_{t+1})\,\alpha\,\frac{Y_{t+1}}{K_{t+1}} + 1 - \delta^K\right)\right]$
Capital accumulation	$K_{t+1} = \left(1 - \delta^K\right) K_t + I_t$
Resource constraint	$(1 - g_t)\, Y_t = C_t + I_t$
Stock market value	$Stock_t = K_{t+1}$

where A_t and Z_t follow stochastic processes given by

$$\log A_t = \rho_A \log A_{t-1} + u_{At},$$

$$\Delta \log Z_t = \rho_Z \Delta \log Z_{t-1} + u_{Zt-1}.$$

Note the timing of the shocks. On the one hand, the variable u_{At} is a transitory surprise technology shock whose innovation has an immediate impact on the level of TFP. On the other hand, the variable u_{Zt} is a permanent news shock whose innovation has no contemporaneous effects on the level of TFP but diffuses slowly into TFP with a time lag.

The government consumes a share g_t of private output, where g_t is an exogenous, random variable following a stationary process,

$$\log g_t = (1 - \rho_g) \log \bar{g} + \rho_g \log g_{t-1} + u_{gt}.$$

The government maintains a balanced budget in every period. I omit derivation of the first-order conditions because they are entirely standard. Because capital is the only asset in this economy and because there are no capital adjustment costs, the value of the aggregate stock market $Stock_t$ is defined as

$$Stock_t \equiv K_{t+1}.$$

The model is summarized in Table 1. The eight equations in the table jointly determine the equilibrium dynamics of the eight variables Y_t, C_t, H_t, I_t, K_t, λ_t, TFP_t, and $Stock_t$.

1.2 Two-Sector Model

The one-sector model is extended to the two-sector model by enriching the supply side. Final good Y_t is produced by a representative competitive final good aggregator with a CES technology:

$$Y_t = \left[\int_{\omega \in \Omega_t} y_t(\omega)^{\frac{\theta-1}{\theta}} d\omega \right]^{\frac{\theta}{\theta-1}}, \tag{1}$$

where Ω_t denotes the set of differentiated products available for production in period t. The cost minimization problem leads to a downward sloping demand curve

$$y_t(\omega) = \left(\frac{p_t(\omega)}{P_t} \right)^{-\theta} Y_t$$

for each available product, where $p_t(\omega)$ denotes the nominal price of $y_t(\omega)$ and P_t denotes the aggregate price index given by

$$P_t = \left[\int_{\omega \in \Omega_t} p_t(\omega)^{1-\theta} d\omega \right]^{\frac{1}{1-\theta}}.$$

Each intermediate good is produced by an atomistic producer or producers depending on the good's location in life cycle. Specifically, I assume that a product is monopolistically produced initially but is later competitively produced. I call products in the first stage of the product cycle "innovative products" and products in the second stage of the product cycle "maturing products." The production function of an intermediate product is given by

$$y_t(\omega) = A_t k_t(\omega)^{\alpha} h_t(\omega)^{1-\alpha}.$$

Cobb–Douglas technology implies that the real marginal cost of producing an intermediate product is given by

$$MC_t = \frac{1}{A_t} \left(\frac{R_t}{\alpha} \right)^{\alpha} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha}.$$

The producer of an innovative product chooses nominal price p_t^I to maximize the profits defined as

$$d_t \equiv \max_{p_t^I} \left(\frac{p_t^I}{P_t} - MC_t \right) \left(\frac{p_t^I}{P_t} \right)^{-\theta} Y_t.$$

She obtains the optimal markup pricing,

$$\frac{p_t^I}{P_t} = \frac{\theta}{\theta-1} MC_t. \tag{2}$$

A producer of a maturing product sets the nominal price p_t^M at the nominal marginal cost because competition drives profits to zero:

$$\frac{p_t^M}{P_t} = MC_t.$$

Let N_t^I denote the mass of innovative products and N_t^M denote the mass of maturing products in period t. Their transition rules are given by

$$N_{t+1}^I = (1 - \delta^N)(1 - \sigma)(N_t^I + N_t^E) \tag{3}$$

$$N_{t+1}^M = (1 - \delta^N)(N_t{}^M + \sigma(N_t^I + N_t^E)),$$

where N_t^E denotes the mass of newly invented products in period t. The underlying assumptions are the following: (i) products are innovative when they are invented, (ii) a fraction σ of randomly chosen innovative products evolve into maturing products in every period, and (iii) as in Bilbiie, Ghironi, and Melitz (2012), there is both a time-to-build lag and a death shock; that is, products invented in period t start producing in period $t + 1$, and a fraction δ^N of both randomly chosen innovative and randomly chosen maturing products become permanently unavailable to the economy. Let N_t denote the mass of total products, that is, the measure of Ω_t. Because $N_t = N_t^I + N_t^M$, its transition rule is given by

$$N_{t+1} = (1 - \delta^N)(N_t + N_t^E).$$

Note that $\sigma = 0$ corresponds to an important special case in which products are uniformly innovative, that is, $N_t = N_t^I$. This case is revisited in Section 3.

The household's utility function is the same as before. The flow budget constraint is given by

$$C_t + I_t^K + X_t = (1 - \tau_t)(W_t H_t + R_t K_t + d_t N_t^I). \tag{4}$$

The variable I_t^K denotes investment in physical capital. The variable X_t denotes R&D spending for product developments. New products are created with the technology given by

$$N_t^E = S_t (N_t^I)^{1-\nu} X_t^{\nu},$$

where S_t is the sector-specific productivity shock, following a stationary process,[6]

$$\log S_t = \rho_S \log S_{t-1} + u_{St}.$$

6. Empirical studies find that the contribution of R&D to firm productivity changes over time (e.g., Griliches 2000). I interpret such changes as evidence of stochastic R&D productivity and introduce a sector-specific productivity shock to capture this notion.

This product innovation function is simple and flexible, accommodating two interesting cases. When $\nu = 1$, product entries increase in a linear fashion with R&D spending as in Bilbiie, Ghironi, and Melitz (2012). This special case is revisited in Section 3. When $0 < \nu < 1$, the product innovation function exhibits diminishing returns to scale in R&D spending, but at the same time, marginal product innovation efficiency of R&D spending improves with the stock of innovative products. I interpret the latter effect as knowledge spillover because a larger stock of innovative products facilitates product developments.

The first-order conditions are given by

$$\frac{1}{C_t - bC_{t-1}} - \lambda_t + E_t\left[\beta\left(\frac{-b}{C_{t+1} - bC_t}\right)\right] = 0 \tag{5}$$

$$\lambda_t (1 - \tau_t) W_t = \psi_t H_t^{\frac{1}{\eta}} \tag{6}$$

$$\lambda_t = E_t\left[\beta\lambda_{t+1}\left((1 - \tau_{t+1}) R_{t+1} + 1 - \delta^K\right)\right] \tag{7}$$

$$-\lambda_t + \eta_t\left(1 - \delta^N\right)(1 - \sigma)\,\nu\frac{N_t^E}{X_t} = 0 \tag{8}$$

$$\begin{aligned} -\eta_t + E_t\Bigg[\ \beta\ \Bigg(&\lambda_{t+1}(1 - \tau_{t+1}) d_{t+1} + \eta_{t+1}\left(1 - \delta^N\right)(1 - \sigma) \\ &\times\left(1 + (1 - \nu)\frac{N_{t+1}^E}{N_{t+1}^I}\right)\Bigg)\Bigg] = 0, \end{aligned} \tag{9}$$

where η_t and λ_t are Lagrangian multipliers for (3) and (4), respectively. Equation (5) equates λ_t with the marginal utility of consumption. Equation (6) is the standard intratemporal optimality condition, and (7) is the standard intertemporal optimality condition. Equation (8) is the optimality condition for R&D spending. Notice that η_t is the marginal utility of innovative products available in the next period. As $\left(1 - \delta^N\right)(1 - \sigma)$ is the probability that an innovative product in the current period remains an innovative product in the next period, and $\nu N_t^E / X_t$ is the marginal product of R&D spending, measured in units of innovative products, (8) equates the opportunity cost of increasing R&D spending by one unit with the marginal benefit of R&D spending. Equation (9) is the first-order optimality condition for the stock of innovative products. It states that the benefit of adding an innovative product in the next period must equal the opportunity cost.

The government behaves in the same way as in the one-sector model. Competitive equilibrium is defined in a standard way. Using both symmetry of products in each group and the market clearing conditions for factor markets, I rewrite the aggregate production function (1):

$$Y_t = (TFP_t)\, K_t^{\alpha} H_t^{1-\alpha},$$

where TFP is given by

$$TFP_t = A_t N_t^{\frac{1}{\theta-1}} \left[\frac{N_t^I}{N_t} + \frac{N_t^M}{N_t} \left(\frac{\theta}{\theta-1} \right)^{\theta-1} \right]^{\frac{\theta}{\theta-1}} \left[\frac{N_t^I}{N_t} + \frac{N_t^M}{N_t} \left(\frac{\theta}{\theta-1} \right)^{\theta} \right]^{-1}.$$

These are key equations. Note that exogenous news shock in the one-sector model, Z_t, is replaced by an endogenous mechanism. Specifically, the level of TFP is affected by the number of products, N_t, and the composition of products, N_t^I/N_t. This is the main idea behind the proposition that sector-specific productivity shock in the two-sector model can be thought of as news shock. Because there is a time-to-build lag in product development, a sector-specific productivity shock does not have a contemporaneous effect on the level of TFP; rather, as it sluggishly affects the number and composition of products with a time lag, a sector-specific productivity shock slowly diffuses into TFP similarly to how a news shock does in the one-sector model. I will show that dynamic responses of TFP to these shocks are not only qualitatively but also quantitatively similar under reasonable calibration.[7]

Combining the household budget constraint and the goods market clearing condition yields the income account,

$$Y_t = W_t H_t + R_t K_t + d_t N_t^I. \tag{10}$$

Aggregate output is equal to the sum of the income generated by production. An interesting observation about this model economy is that, unlike in standard neoclassical growth models, income shares are not constant but fluctuate endogenously. Specifically, dividend income is written

$$d_t N_t^I = \frac{Y_t}{\theta} \frac{N_t^I}{N_t} \left[\frac{N_t^I}{N_t} + \frac{N_t^M}{N_t} \left(\frac{\theta}{\theta-1} \right)^{\theta-1} \right]^{-1}.$$

The remaining income is divided between capital and labor in constant shares. Therefore, factor shares are affected by the composition of products. Specifically, the dividend share increases with the share of innovative products in total products, and both

7. Long-run implications are different because a news shock in the one-sector model has a permanent effect on TFP, while a sector-specific productivity shock in the two-sector model does not. However, they generate similar dynamic responses of TFP at high, medium, and low frequencies, at least up to 200 quarters. Therefore, the difference in the permanent future is not an especially serious concern for the current study as long as the focus is on fluctuations.

capital and labor shares decrease with the share of innovative products in total products. Changes in this intensive margin turn out to be a very powerful amplification mechanism.

I define investment I_t as the sum of investment in physical capital and product developments:[8]

$$I_t = I_t^K + X_t.$$

The value of the aggregate stock market $Stock_t$ is defined as the sum of capital stock and the value of innovative products,[9]

$$Stock_t \equiv K_{t+1} + q_t \left(N_t^I + N_t^E\right),$$

q_t is the price of an innovative product available at the end of period t. More specifically, it is defined as $q_t \equiv (1-\delta^N)(1-\sigma)\eta_t/\lambda_t$, and is determined by the following pricing equation, derived from the household's first-order condition (9):

$$q_t = E_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\left(1-\delta^N\right)(1-\sigma) \times \left((1-\tau_{t+1})d_{t+1} + q_{t+1}(1-\nu)\frac{N_{t+1}^E}{N_{t+1}^I} + q_{t+1}\right)\right]. \quad (11)$$

This equation illustrates the innovative product's dual role. On the one hand, an innovative product is a monopolistic product generating a sequence of profits. Let v_t denote the asset value of an innovative product focusing on this aspect, which is given by

$$v_t = E_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\left(1-\delta^N\right)(1-\sigma)\left((1-\tau_{t+1})d_{t+1} + v_{t+1}\right)\right]. \quad (12)$$

On the other hand, an innovative product is a useful input in the R&D sector. Let $\tilde{v}_t$ denote the asset value of an innovative product focusing on this aspect, which is given by

$$\tilde{v}_t = E_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\left(1-\delta^N\right)(1-\sigma)\left((v_{t+1}+\tilde{v}_{t+1})(1-\nu)\frac{N_{t+1}^E}{N_{t+1}^I} + \tilde{v}_{t+1}\right)\right]. \quad (13)$$

It is clear that $q_t = v_t + \tilde{v}_t$ because adding (12) and (13) leads to (11).

8. I include product development costs to investment, following Bilbiie, Ghironi, and Melitz (2012). McGrattan and Prescott (2010) do not include intangible investment in the measured investment but treat it as business spending instead.

9. The assumption that new products are immediately added to the stock market is counterfactual. The working paper version of the current manuscript (Jinnai 2013), however, demonstrates that the results are reasonably robust to alternative definitions of the stock market value.

TABLE 2
Two-Sector Model Summary

Production	$Y_t = (TFP_t)\, K_t^{\alpha} H_t^{1-\alpha}$
TFP	$TFP_t = A_t N_t^{\frac{1}{\theta-1}} \left[\frac{N_t^I}{N_t} + \left(1 - \frac{N_t^I}{N_t}\right)\left(\frac{\theta}{\theta-1}\right)^{\theta-1}\right]^{\frac{\theta}{\theta-1}} \left[\frac{N_t^I}{N_t} + \left(1 - \frac{N_t^I}{N_t}\right)\left(\frac{\theta}{\theta-1}\right)^{\theta}\right]^{-1}$
Consumption	$\frac{1}{C_t - bC_{t-1}} - \lambda_t + E_t\left[\beta\left(\frac{-b}{C_{t+1} - bC_t}\right)\right] = 0$
Hours	$\lambda_t (1 - g_t) \frac{(1-\alpha)\left(Y_t - d_t N_t^I\right)}{H_t} = \psi_t H_t^{\frac{1}{\eta}}$
Euler equation	$\lambda_t = E_t\left[\beta\lambda_{t+1}\left((1 - g_{t+1}) \frac{\alpha\left(Y_{t+1} - d_{t+1} N_{t+1}^I\right)}{K_{t+1}} + 1 - \delta^K\right)\right]$
Capital accumulation	$K_{t+1} = \left(1 - \delta^K\right) K_t + I_t^K$
R&D spending	$X_t = (v_t + \tilde{v}_t)\, \nu N_t^E$
Monopoly value	$\lambda_t v_t = E_t\left[\beta\lambda_{t+1}\left(1 - \delta^N\right)(1 - \sigma)\left((1 - g_{t+1})\, d_{t+1} + v_{t+1}\right)\right]$
R&D value	$\lambda_t \tilde{v}_t = E_t\left[\beta\lambda_{t+1}\left(1 - \delta^N\right)(1 - \sigma)\left((v_{t+1} + \tilde{v}_{t+1})(1 - \nu) \frac{N_{t+1}^E}{N_{t+1}^I} + \tilde{v}_{t+1}\right)\right]$
Dividend	$d_t N_t^I = \frac{Y_t}{\theta} \frac{N_t^I}{N_t} \left[\frac{N_t^I}{N_t} + \left(1 - \frac{N_t^I}{N_t}\right)\left(\frac{\theta}{\theta-1}\right)^{\theta-1}\right]^{-1}$
Product innovation	$N_t^E = S_t \left(N_t^I\right)^{1-\nu} (X_t)^{\nu}$
Innovative products	$N_{t+1}^I = \left(1 - \delta^N\right)(1 - \sigma)\left(N_t^I + N_t^E\right)$
Total products	$N_{t+1} = \left(1 - \delta^N\right)\left(N_t + N_t^E\right)$
Resource constraint	$(1 - g_t)\, Y_t = C_t + I_t^K + X_t$
Investment	$I_t = I_t^K + X_t$
Stock market value	$Stock_t = K_{t+1} + (v_t + \tilde{v}_t)\left(N_t^I + N_t^E\right)$

The model is summarized in Table 2. The 16 equations in the table jointly determine the equilibrium dynamics of 16 endogenous variables, Y_t, C_t, I_t, I_t^K, X_t, K_t, H_t , λ_t, d_t, N_t^I, N_t^E, N_t, v_t, $\tilde{v}_t$, TFP_t, and $Stock_t$.

1.3 Calibration

Calibration is summarized in Table 3. The parameters are divided into three groups. The first group lists parameters that are common to both the one- and two-sector models. For those parameters, I follow Barsky and Sims (2011) and set them at $\beta = 0.99$, $b = 0.8$, $\eta = 1$, $\delta^K = 0.025$, $\alpha = 0.33$, $\bar{g} = 0.2$, $\rho_g = 0.95$, $\rho_\psi = 0.8$, and the standard deviations of u_{gt} and $u_{\psi t}$ at 0.15% .

The parameters in the second group are unique to the two-sector model. There are four such parameters. I set the size of the death shock at $\delta^N = 0.025$ and the elasticity of substitution between products at $\theta = 3.8$, following Bilbiie, Ghironi, and Melitz (2012). I set the transition probability of an innovative product becoming a maturing product at $\sigma = 1/80$ so that the average duration of a product being innovative matches the official patent term. The research elasticity ν is calibrated to match the ratio of R&D spending to corporate profits, which is approximately constant in the data. The model counterpart increases in ν, taking a value from zero

TABLE 3

CALIBRATION

Common parameters		One sector	Two sector
β	Time discount factor	0.99	0.99
b	Degree of habit	0.8	0.8
η	Elasticity of leisure	1	1
δ^K	Capital depreciation rate	0.025	0.025
α	Capital elasticity	0.33	0.33
$\bar{g}$	Average government spending share	0.2	0.2
σ_{u_g}	Standard deviation of u_{gt}	0.0015	0.0015
ρ_g	Persistence of log g_t	0.95	0.95
σ_{u_ψ}	Standard deviation of $u_{\psi t}$	0.0015	0.0015
ρ_ψ	Persistence of log ψ_t	0.8	0.8
Parameters unique to the two-sector model			**Two sector**
δ^N	Death shock		0.025
θ	Elasticity of substitution between products		3.8
σ	Maturation rate		1/80
ν	Research elasticity		0.175
Parameters calibrated to match TFP response		**One sector**	**Two sector**
σ_{u_A}	Standard deviation of u_{At}	0.0075	0.0075
ρ_A	Persistence of log A_t	0.980	0.978
σ_{u_Z}	Standard deviation of u_{Zt}	0.00098	
ρ_Z	Persistence of Δ log Z_t	0.822	
σ_{u_S}	Standard deviation of $u_{S,t}$		0.0910
ρ_S	Persistence of log S_t		0.806

to nearly two-thirds given our calibration of β, δ^N, σ, and $\bar{g}$. Our target value is 0.313.[10] Hence, I set ν at $\nu = 0.175$.

The parameters in the third group are those governing technology shocks. For the one-sector model, they are parameters determining stochastic processes of surprise technology shock A_t and news shock Z_t. These are calibrated to match the dynamic properties of TFP reported by Barsky and Sims (2011). Specifically, I set $\rho_A = 0.98$ and the standard deviation of u_{At} at 0.75% so that the model-implied impulse response of TFP to a surprise technology shock matches the empirically observed impulse response of TFP to its own innovation.[11] I set $\rho_Z = 0.822$ and the standard deviation of u_{Zt} at 0.098% so that the model-implied share of the forecast error variance of TFP attributable to news shock at various forecast horizons matches its empirical counterpart.

For the two-sector model, the parameters determine the stochastic processes of neutral productivity shock A_t and sector-specific productivity shock S_t. These are calibrated so that the impulse responses of TFP are similar across models. Specifically, I set $\rho_A = 0.978$ and the standard deviation of u_{At} at 0.75% so that a neutral productivity shock in the two-sector model and a surprise technology shock in the

10. This is the historical average of the ratio of total domestic R&D to corporate profits with inventory valuation adjustment and capital consumption adjustment. Both series are taken from the Bureau of Economic Analysis.

11. See Barsky and Sims (2011, p. 287).

one-sector model generate similar dynamic responses of TFP. The standard deviations are set at the same value so that the initial responses to a one standard deviation innovation to each shock are identical. The persistence is slightly lower in the two-sector model because product entries add extra persistence in the two-sector model. Similarly, I set the persistence of the sector-specific productivity shock at $\rho_S = 0.806$ and the standard deviation of u_{St} at 9.10% so that a sector-specific productivity shock in the two-sector model and a news shock in the one-sector model generate similar dynamic responses of TFP. A small value of ρ_S indicates that the model contains a strong, endogenous amplification mechanism.

2. RESULTS

I start my analysis by running the Barsky and Sims (2011) VAR with the artificially generated data. First, I simulate the model economies and generate artificial time series for TFP, consumption, output, and hours. Then, I estimate the VAR model with the simulated data and apply the same decomposition as in Barsky and Sims. I run this 1,000 times, and in Figure 1, I report the average impulse response functions along with the estimates of Barsky and Sims. Impulse response functions obtained in this experiment are similar to their empirical counterparts; they are for the most part contained in the one standard deviation confidence bands. An exception is TFP, for which the impulse response functions, estimated with the simulated data, overshoot the confidence band at medium frequencies. In fact, these impulse response functions are consistent with the empirical evidence in an extended VAR model that Barsky and Sims consider and that I target in the calibration.[12] Reducing the size of the standard deviation of news shocks in the one-sector model or reducing the size of the standard deviation of sector-specific productivity shocks in the two-sector model makes the simulation-based impulse response function of TFP in the corresponding model more similar to the empirical counterpart in the baseline model, while leaving the responses of other variables largely within the one standard deviation confidence bands.[13] The two models are, therefore, largely consistent with the empirical evidence.

Figure 2 plots theoretical impulse response functions to a news shock in the one-sector model and theoretical impulse response functions to a sector-specific productivity shock in the two-sector model. Notice that they are nearly identical to the impulse response functions observed in the previous experiment using the corresponding model, indicating that Barsky and Sims's (2011) decomposition correctly identifies news shocks when it is applied to the one-sector model, but identifies and labels sector-specific productivity shocks as news when it is applied to the two-sector

12. In the extended model, three information variables, that is, stock price, consumer confidence, and inflation, are added to the baseline model.

13. Detailed results are available upon request.

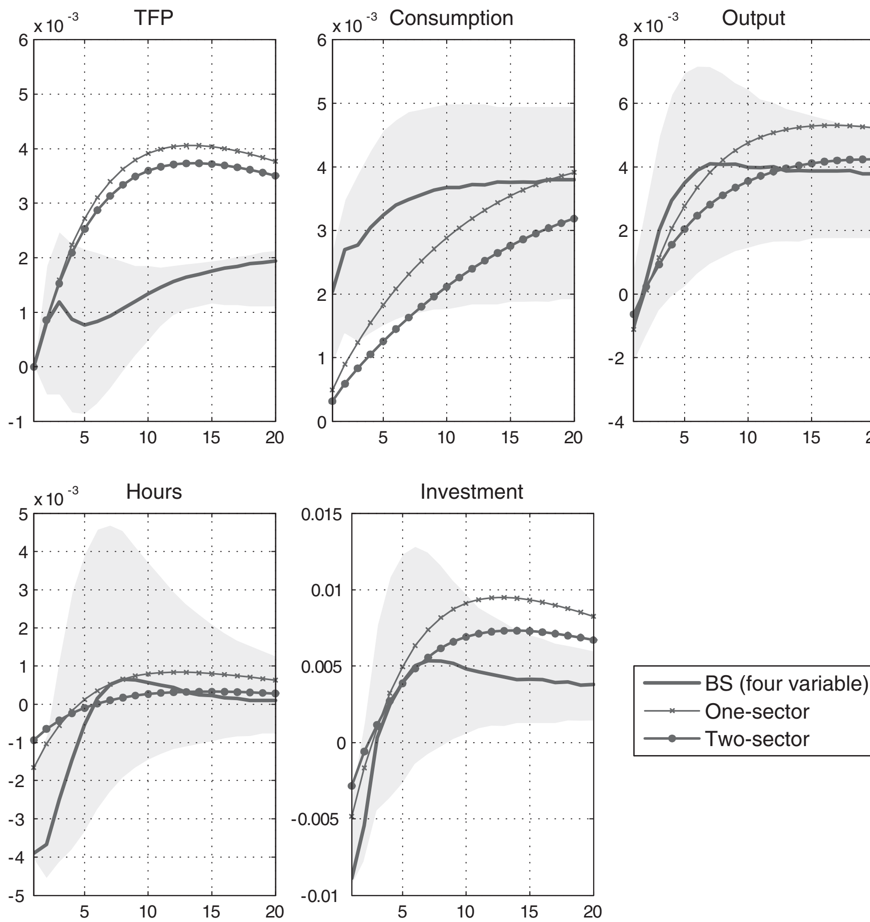

FIG. 1. Barsky and Sims (2011) Decomposition Applied to the Simulated Data.

NOTES: Lines with circles are from the two-sector model; lines with crosses are from the one-sector model. Solid lines are the estimates of Barsky and Sims (2011) with four-variable VAR, and gray areas are ± one standard deviation confidence bands. The investment response, in all cases, is imputed as the output response minus the share-weighted consumption response.

model. This is because Barsky and Sims's decomposition extracts a shock that is neutral to the TFP measure in the first quarter but best explains variations in TFP for all horizons between two and forty quarters. Both news shocks in the one-sector model and sector-specific productivity shocks in the two-sector model have this property.

Figure 2 also plots theoretical impulse response functions of the aggregate stock market. In the one-sector model, the aggregate stock market value falls on impact of a news shock, whereas in the two-sector model, it rises on impact of a sector-specific productivity shock. While these responses are not quantitatively very large,

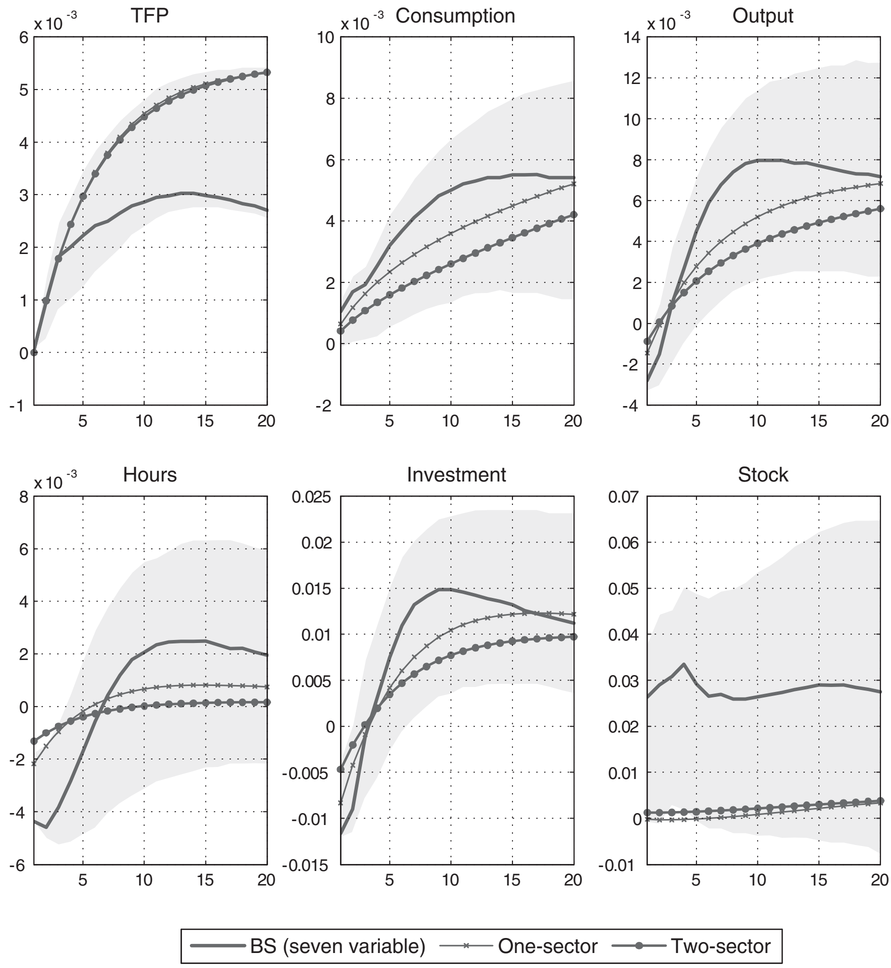

FIG. 2. Impulse Responses to a Sector-Specific Productivity Shock in the Two-Sector Model (Lines with Circles), and Impulse Responses to a News Shock in the One-Sector Model (Lines with Crosses).

NOTES: Solid lines are the estimates of Barsky and Sims (2011) for the seven-variable VAR, and gray areas are ± one standard deviation confidence bands. Barsky and Sims impute the investment response as the output response minus the share-weighted consumption response.

the empirical evidence is more supportive of the qualitative prediction of the two-sector model than of the one-sector model. That is, as plotted in the same figure, Barsky and Sims (2011) find that the aggregate stock market index rises on impact of their identified news shock. This response is caused by an increase in the value of innovative products in the R&D sector. The other half of innovative products' value, that is, their value as monopolistic products, decreases due to the impact of a

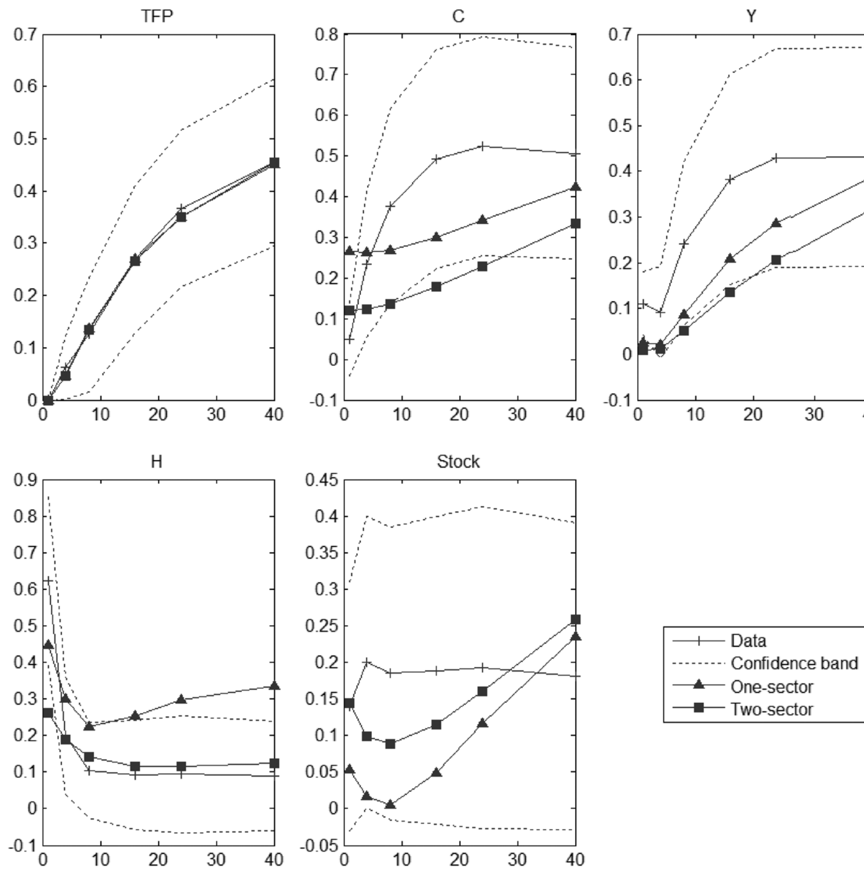

FIG. 3. Forecast Error Variance Decompositions.

NOTES: The horizontal axis measures the forecast horizon. Estimates of Barsky and Sims (2011) are referred to as data, which are the fraction of the forecast error variance of each variable at various forecast horizons (1, 4, 8, 16, 24, and 40 quarters) attributable to identified news shock in their VAR model. One standard error confidence band is taken from Basky and Sims. The other two lines show the fraction of the forecast error variance attributable to news shock in the one-sector model and the fraction of the forecast error variance attributable to sector-specific productivity shock in the two-sector model, respectively.

sector-specific productivity shock because product entries dilute per product monopoly profits.[14]

Figure 3 shows forecast error variance decomposition. Five panels report the forecast error variance decomposition of five important variables, that is, TFP, consumption, output, hours, and aggregate stock market value. There are three lines and a confidence band in each panel. One line is data, taken from Barsky and Sims (2011),

14. See Jinnai (2013) for details.

depicting the fraction of the forecast error variance attributable to an identified news shock in their VAR model. One standard error confidence band is also taken from Barsky and Sims. The two remaining lines show theoretical predictions from each of the two models, that is, the fraction of the forecast error variance attributable to news shock in the one-sector model and the fraction of the forecast error variance attributable to sector-specific productivity shock in the two-sector model.[15] The three lines are almost perfectly overlapped in the top-left panel, which reports the forecast error variance decomposition of TFP. This overlap in the three lines is due to the calibration.

Barsky and Sims's (2011) estimates of the contribution of identified news shock vary not only across variables but also across forecast horizons. At short horizons, identified news shocks account for a very small share of the forecast error variances of consumption and output, a large share of the forecast error variances of hours, and a modest share of the forecast error variances of aggregate stock market value. At longer horizons, the identified news shock contributes more significantly to the variance decomposition of aggregate variables with the exception of hours, in which the contributions of news shocks are quickly weakened, resulting in an L-shaped plot.

The one-sector model successfully replicates the general pattern of the data. In particular, the model's prediction that news shocks become more important in accounting for variations of TFP, consumption, and output at longer forecast horizons is in line with the data. However, a closer examination reveals three important discrepancies between the model's predictions and the data. First, the one-sector model overemphasizes news shocks' contributions to the forecast error variance of consumption at a very short horizon. Second, the one-sector model predicts that news shocks make a significant contribution to the variance decomposition of hours at both short and long horizons, resulting in a V-shaped plot. Third, the one-sector model predicts that news shocks account for a negligible share of the forecast error variances of the aggregate stock market value at short horizons, with nearly zero contribution 2 years after a shock.

Interestingly, all three problems largely disappear in the two-sector model. First, sector-specific productivity shocks account for a smaller share of the forecast error variance of consumption at short horizons. This is because, as product development is investment, the resource constraint does not allow consumption to increase after a sector-specific productivity shock as much as it does after a news shock in the one-sector model. Second, sector-specific productivity shocks make weaker contributions to the forecast error variance of hours at medium frequencies. The product cycle plays an important role, meaning that because TFP improvement is achieved by high product entry rates but new products are monopolistically produced, producers of

15. Because I set the standard deviations of both the government spending shock and the preference shock to small values, my calibration implicitly assumes that productivity shocks account for most of the variation of the aggregate variables. If our model economies can replicate the general patterns in the data under this assumption, they arguably offer the simplest interpretation of the data.

new products do not hire as many hours as competitive firms in the one-sector model do after a news shock. Third, sector-specific productivity shocks account for a large share of the forecast error variance of the aggregate stock market value. This is because a sector-specific productivity shock generates a positive impact response of the aggregate stock market value consistent with the data.

3. DISCUSSIONS

3.1 Roles of Heterogeneous Products and Knowledge Spillover

This section closely examines the roles of heterogeneous products and knowledge spillover. Heterogeneity results from the product cycle; hence, one way to determine its significance is to experiment with a parameter configuration that shuts the product cycle down, that is, setting σ to $\sigma = 0$. Products are uniformly innovative under this calibration. I keep the other parameters set to the same values, except those governing technology shocks, which are recalibrated so that the impulse response functions of TFP under the alternative calibration resemble those under the benchmark calibration. Figure 4 shows that when the parameter σ is set at zero, many variables respond differently to a sector-specific productivity shock relative to the benchmark calibration, indicating that the product cycle is a powerful amplification mechanism.

The most striking difference is the response of the aggregate stock market value. While it rises on impact of a sector-specific productivity shock under the benchmark calibration, it falls under the alternative calibration. The key to understanding this difference is to understand the changes in product composition. Recall that the dividend income share increases with the share of innovative products in total products. Under the benchmark calibration, a sector-specific productivity shock has a strong effect on dividend income because new products are innovative, and therefore the shares of innovative products and of dividend income increase after the shock. Although high product entry rates dilute per product monopoly profits, the above-mentioned mechanism prevents a catastrophic crash in the value of innovative products as monopolistic products. Under the alternative calibration, however, this amplification mechanism is inactive. Fluctuations in dividend income are greatly limited, and hence a sector-specific productivity shock leads to a larger decrease in the value of innovative products as monopolistic products.

Next, I examine the role of knowledge spillover, by experimenting with an alternative parameter configuration, specifically, with $\nu = 1$. Under this calibration, product entry increases in linear fashion with R&D spending. No diminishing returns to scale set in, and the efficiency of product innovation is unaffected by the stock of innovative products. The other parameters are set at the same values, with the exception of those governing technology shocks, which are recalibrated so that the impulse response functions of TFP resemble those under the benchmark calibration. Figure 4 shows that responses of TFP cannot be perfectly matched because the alternative

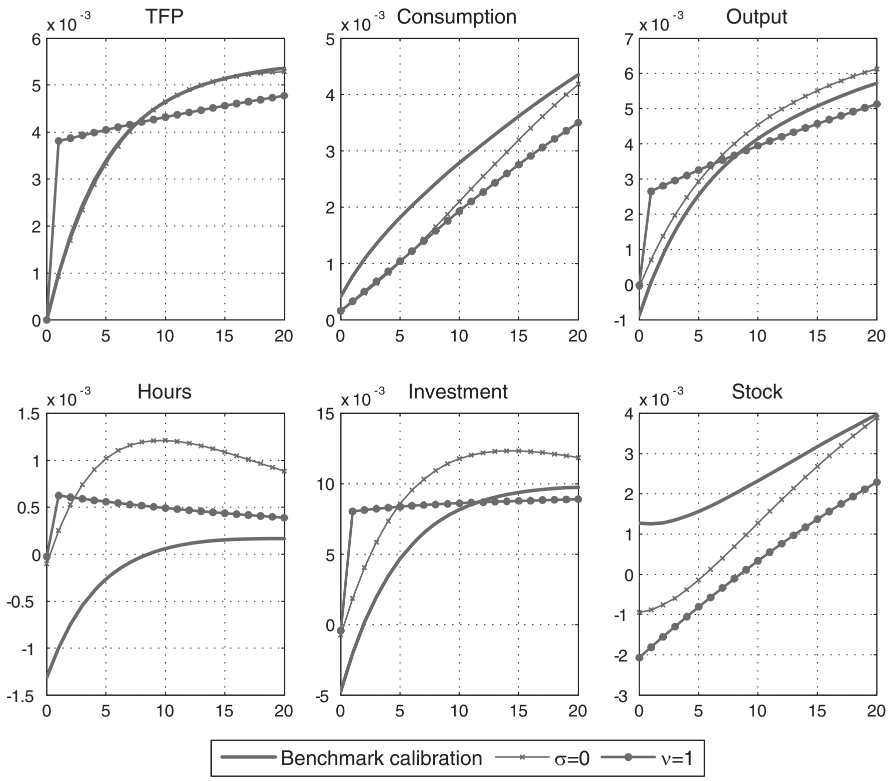

FIG. 4. Impulse Responses to a Sector-Specific Productivity Shock under Alternative Calibrations.

NOTES: Log deviations from steady state are plotted.

calibration removes persistence. The lack of persistence indicates the importance of knowledge spillover as an amplification mechanism.

Once again, responses of the aggregate stock market value are strikingly different. Although aggregate stock market value rises on impact of a sector-specific productivity shock under the benchmark calibration, under the alternative calibration, it falls. The cause is easily understood. Under the benchmark calibration, the aggregate stock market value is decomposed into three parts: the value of the capital stock, the value of innovative products as monopolistic products, and the value of innovative products in the R&D sector. Among these three parts, only the last, the value of innovative products in the R&D sector, responds positively to sector-specific productivity shocks. Under the alternative calibration, however, innovative products have no use in the R&D sector. Without a capital gain in the value of innovative products in the R&D sector, a sector-specific productivity shock leads to a crash in the aggregate stock market value.

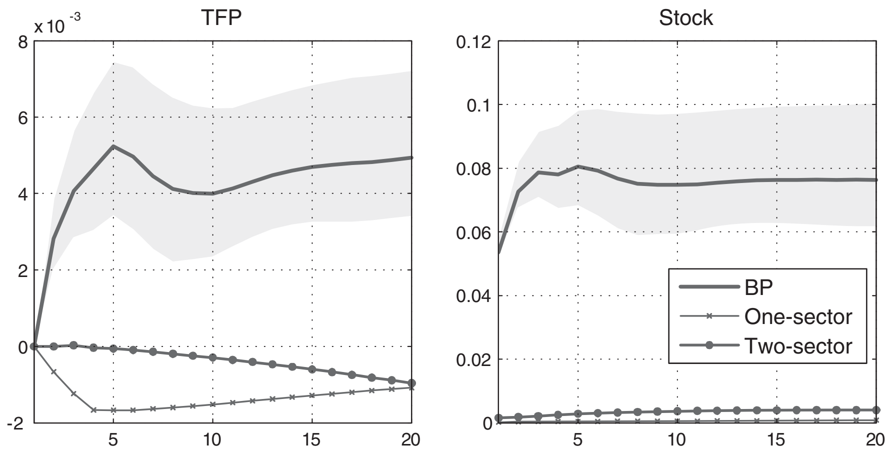

Fig. 5. Beaudry and Portier's (2006) Short-Run Identification Applied to the Artificially Simulated Data.

Notes: Lines with circles are from the two-sector model; lines with crosses are from the one-sector model. Solid lines are the estimates of Beaudry and Portier (2006) in the (*TFP*, *Stock*) VECM, and gray areas represent the 80% confidence band.

3.2 Model's Ability to Reproduce Beaudry and Portier's (2006) Evidence

In this section, I ask whether the model economies can reproduce the empirical findings in Beaudry and Portier (2006). Specifically, I run the following experiment. I simulate the model economies, generating artificial time series for TFP and aggregate stock market value. I then run the Beaudry–Portier VAR with the simulated data and apply the short-run decomposition, which identifies a stock market innovation that is contemporaneously orthogonal to TFP. I run this 1,000 times, and in Figure 5, I report the average impulse response functions, along with the estimates of Beaudry and Portier. The figure shows that neither the one-sector model nor the two-sector model can account for the Beaudry–Portier findings. The impulse response functions of the aggregate stock market value lie far outside the confidence band. In the experiment with the one-sector model, an orthogonalized stock market innovation is associated with quick and large negative responses of TFP in the future. While such responses of TFP resemble the theoretical impulse responses to negative news shocks in the one-sector model, they are inconsistent with the empirical evidence. In the experiment with the two-sector model, an orthogonalized stock market innovation is associated with a slight increase in TFP in the first few quarters after the shock, but with negative responses of TFP in subsequent periods. These responses are neither consistent with the empirical evidence nor similar to any of the theoretical impulse responses to the structural shocks in the model economy. This result indicates that the bivariate VAR model is not flexible enough to adequately capture the complex dynamics of the two-sector model. I also run the same experiment with the VAR model, estimated using the level specification, and find essentially the same results. These results suggest that

Beaudry and Portier might identify one of the other types of news shocks proposed in the literature, but not considered in this paper.

4. CONCLUSION

Most of the theoretical work in the news shock literature abstracts away from structural explanations, assuming instead that good news is a pure signal giving agents advance notice that aggregate technology will undergo exogenous change at some future point. This assumption is convenient for the purposes of introducing optimism and pessimism into the rational expectation model. However, such an assumption is arguably unrealistic, and without a structure detailing the cause of future technological progress, analysis based on this assumption may lead to misguided policy recommendations.

Searching for a structural explanation for news is therefore important, and the current paper contributes to that search. Specifically, it proposes that a surprise improvement in sector-specific productivity in the R&D sector can be seen as news about aggregate productivity. I believe that the proposed mechanism is reasonable and that the model's ability to match data is largely satisfactory. But there are other possibilities that can explain news equally well. For example, Comin, Gertler, and Santacreu (2009) explore an alternative explanation, proposing an unexpected advancement of the technology frontier as news that slowly diffuses to the economy through the costly implementation of new ideas. Exploring such competing explanations will lead to a better understanding of news, the source of technological progress, and the source of economic fluctuations.

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