Technology creation and monetary transmission*

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Abstract

We build and embed an endogenous growth mechanism into an otherwise standard New Keynesian DSGE model to investigate the transmission of monetary policy. Endogenous growth is determined by the R&D expenditures of monopolistically competitive firms and monetary policy, through its effects on these expenditures, can have supply side effects in addition to its usual demand side effects. After solving the model and estimating it with a Bayesian methodology, we find that R&D activity amplifies the responses to monetary policy shocks. An empirical investigation that uses firm-level COMPUSTAT data provides support for this result. Specifically, we find that monetary policy transmission operates more strongly through R&D intensive firms.

Keywords: R&D, endogenous growth, DSGE, monetary policy, COMPUSTAT.

Classifications: E24, E32, O30, O33.

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1 Introduction

It is well-established that technology creation and innovation-induced productivity are procyclical (e.g., Aghion and Saint-Paul, 1998; Fernald, J. G., 2014; Christiano et al., 2015; Anzoategui et al., 2019). It is equally well-understood that business cycles are primarily driven by demand and financial shocks (Keynes, 1936; Blanchard and Quah,1989; Jorda et al., 2013). The two sets of observations then imply that demand and financial shocks can alter the growth path of the economy by impacting technology creation. There is ample evidence supporting this link (Cerra and Saxena, 2008; DeLong and Summers, 2012; Fatás and Mihov, 2013). In this paper, we take a less-travelled path, and show that the relationship between technology creation and a demand side shock can also have implications for short-term economic fluctuations in addition to its long-term growth effects. In particular, we theoretically show that Research and Development (R&D) activity, the input of technology creation, can amplify the output responses to a monetary policy shock, a demand side shock, and find quantitatively important firm-level evidence that support this relationship. The central inference from our paper is that while shocks to the side supply side of the economy may be less important for business cycles, innovative activity on this side of the economy forms an important conduit through which demand side shocks, such as monetary policy shocks propagate.

To identify and investigate the link between R&D and business cycles, we embed an endogenous growth mechanism into a New Keynesian dynamic stochastic general equilibrium (DSGE) model. The endogenous growth mechanism, and especially the DSGE setup in our model are not new. It is the combination of the two, however, that is relatively rare in the literature and investigating monetary transmission within this model is the unique feature of our paper. In this model, economic growth is generated by an innovation process that takes R&D activity as the input. If R&D activity successfully results in an innovation, this increases firms' stock of knowledge that in turn augments labor efficiency. The solution to the model reveals a key disparity between the marginal benefits of R&D activity and production labor. While the latter exhibits diminishing returns the former does not. This disparity implies that the marginal benefits to R&D is more responsive to systematic shocks in the economy and that a smaller response in R&D activity is sufficient to match the change in the marginal returns to production labor. This mechanism is reinforced by the knowledge accumulation process. R&D affects efficiency and marginal benefits not only today but also in future periods and thus firms exhibit a stronger R&D smoothing behavior in response to highly responsive and persistent benefits to this activity. Monetary policy, through its affects on the real interest, plays a crucial role here as it causes future benefits of R&D to be discounted at a lower rate during a monetary expansion and at a higher rate during a monetary tightening, further mitigating R&D responsiveness.

Estimating the model with and without the endogenous growth mechanism and by using standard macroeconomic data, we first observe that innovation shocks ("standing on shoulders shocks" modelled as a change in the success rate of R&D activity) are inconsequential for output fluctuations. We also observe, however, that monetary policy shocks are substantially more important drivers of business cycles in the model with the endogenous growth mechanism. In the model without R&D, the predictive power of monetary policy shocks is absorbed by price and total factor productivity shocks. These results suggest that while technology shocks may not the primary drivers of business cycles, the technology creation process forms an important channel through which demand side shocks such as monetary policy shocks are transmitted to the economy. Specifically, firms' R&D smoothing behavior in the model generates a larger response in production labor and output supply which allows it to match the changes in demand.

We draw similar inferences from an alternative framework that distinguishes between intermediate good producing firms that create technology and those that adopt. Specifically, the creators' production is much more responsive to monetary policy under different calibrations of the model. Estimating this model, by obtaining data from the COMPUSTAT database and aggregating the data to represent the production of firms that conduct R&D and those that do not, we uncover a stronger monetary transmission through firms that report R&D activity, and a much larger contribution of demand/financial shocks to the variation in these firms' output.

In the second half of the paper, we conduct several empirical analyses by using quarterly firm-level data from the COMPUSTAT, North America database that spans the 2000Q1 to 2023Q4 period and find, similar to the DSGE model results, a positive relationship between R&D intensity and the strength of monetary policy transmission. Using a dynamic panel model, we estimate the effect of monetary policy shocks on firms' real sales growth and investigate how this effect varies with firms' R&D intensity, controlling for firm-level financial variables and covering the period between 2000 and 2023. Our estimates reveal that R&D intensity amplifies the response of sales growth to monetary policy shocks. Quantitatively, the real sales growth of a firm with an R&D-to-assets ratio of 1 percent is roughly 2.5 times more sensitive to monetary policy shocks compared to a firm that does not engage in R&D. By contrast, the sales growth of firms without any R&D expenditures is not significantly responsive to monetary policy shocks.

We proceed by documenting the sales sensitivity to large monetary policy shocks, building on recent studies (Fasani et al., 2024; Anzuini, 2021; Debortoli et al., 2020) that indicate the impact of monetary policy shocks on the economy may not be proportional to their size. For these analyses, we omit shocks that lie within the one-third of a standard deviation band around the mean. Consistent with previous literature, the coefficients for both the monetary policy shock and its interaction with R&D are larger in magnitude than in the baseline results.

In our data set firms that conduct R&D are typically larger in size. To determine whether our results are driven by the disparity in the firms' size or R&D activity, we first separate firms into groups according to their size and R&D intensity. Separately estimating our baseline model by using data for these subgroups, we detect a higher sensitivity to monetary policy for high R&D intensity firms regardless of their size. We then follow a propensity score matching approach that does not rely on assumptions about the functional relationships between monetary policy shocks, firm-level financial variables, and sales growth rates. Our estimations similarly suggest that monetary policy shocks have a more negative impact on sales growth for firms with higher R&D-to-assets ratios. The results suggest that the average sensitivity of sales growth to monetary policy shocks would increase in absolute value by approximately 5 percentage points if a firm transitioned from the low-R&D group to the high-R&D group in our sample.

In the DSGE model and the empirical analyses described above, we use quarterly data to measure short-term volatility. As an alternative exercise, we investigate the implications of R&D activity for volatility at a higher frequency. Using firm-level daily stock prices instead of sales and term premium shocks instead of monetary policy shocks, we find results that are opposite of the ones discussed so far. Specifically, we find that the stock returns for high R&D firms are less sensitive to term premium shocks. The disparity in the results suggests that the implications of R&D activity for economic volatility depends on the time horizon. While R&D intensity can amplify quarterly volatility it can also provide greater stability at the daily frequency.

Our paper is related to a long-standing literature that documents the cyclicality of R&D spending and relates this cyclicality to the opportunity costs of R&D activities along the business cycle. Evidence is mixed with some studies finding/predicting lower opportunity costs, especially for financially constrained firms, during economic downturns (Aghion and Saint-Paul, 1998; Aghion et al., 2012) and some predicting otherwise (Himmelberg and Petersen, 1994; Hall and Lerner, 2010; Rafferty and Funk, 2008) postulating that risky activities such as R&D are more rapidly curbed during an economic contraction. The latter relationship has gained increasing support in the aftermath of the 2008/09 crisis by papers such as Fernald (2014), Queraltó (2013), Christiano et al. (2015), Bianchi et al. (2018), Anzoategui et. al (2019) that investigate and explain the productivity slow-down during and after the crisis. In constructing our model, we adopt some features from these studies. For example, R&D impacts the production function through a labor-augmenting technology as in Bianchi et al. (2018). As in Anzoategui et. al (2018), this technology is also allowed to diffuse across firms (across all firms in the baseline model, and from creators to adopters in the model with heterogenous firms).

Despite the similarities with the literature discussed above, the approach that we take in our paper is fundamentally different. In our paper, we investigate the impact of innovation through R&D on business cycles and not the other way around. While there are few studies (Comin and Gertler, 2006; Kung and Schmid, 2015) that find an empirical link between R&D, trend growth and persistence of output, our analysis, to the best of our knowledge, is the first attempt at associating the amplitude of business cycles with R&D-driven innovation. Focusing on monetary policy, our analysis reveals that the R&D process constitutes an important channel through which monetary policy transmission is strengthened. More generally, our model and empirical results suggest that the standard negative link between short-term volatility and long-term economic growth could be reversed if R&D is the source of economic growth. Specifically, R&D-driven innovation, an unequivocally growth enhancing activity, can at the same time introduce higher short-term volatility.

While we follow a less traveled path when combining short-run and long-run aspects of the economy, we should qualify our modelling contribution by citing previous studies such as Bilbiie et al. (2012), (2008), (2019), Broda and Weinstein (2010) that analyze exit/entry dynamics and endogenous product creation. The models in these papers also feature elements that allow for a joint investigation of short-run dynamics along side those that govern long-run growth. Different from these studies, the source of growth in our model is solely R&D activity and not firms' entry and exit.

Some components and assumptions of our model are informed by microeconomic evidence. Studies such as Foster and Grim (2010) and Foster et al. (2016), for example, demonstrate that R&D activity in the US is mostly conducted by large firms with high market power and multiple production processes that benefit from R&D-driven innovation. There is also evidence uncovering an increasing pace of technology diffusion and outsourcing (e.g. Chesbrough, 2003; Azoulay, 2004; Cassiman and Veugulers, 2006; Knott, 2017). Finally, studies such as Brown et al. (2012), Hall et al. (2016) and Aysun and Kabukcuoglu (2019) point to the R&D smoothing behavior of firms and associate this with high adjustment costs of R&D (relative to physical capital). In our model, R&D is conducted by monopolistically competitive firms that also produce intermediate goods, there are positive costs to adjusting the level of R&D activity, and innovations of firms diffuse to and are adopted by other firms. Our analysis reveals that the R&D smoothing behavior of firms is a crucial source of short-term volatility and that it is R&D activity and not the size of the firms that is significantly related to this volatility.

A majority of the studies on monetary policy transmission have focused on banks given the predictions of the credit channel theory (see, Gertler and Gilchrist, 1994; Bernanke et al., 1996).

There is however a large and increasing number of empirical studies that also focus on the supply side effects of monetary policies and relate the effectiveness of these policies to firm-specific characteristics. Dedola and Lippi (2005) document a significant cross-industry variation in the strength of monetary transmission, with particularly pronounced effects in durable and capital goods sectors. Chatelain et al. (2002) and Durante et al. (2022) find that younger and more leveraged firms contract more strongly in response to monetary tightening, consistent with credit channel predictions. Jeenas (2024) identifies liquidity buffers as another crucial determinant, showing that firms with lower liquidity significantly reduce investment following monetary contractions. Ottonello and Winberry (2020) argue that firms with low default risk and lower leverage are more responsive to monetary shocks. Additionally, Caglio et al. (2022) distinguish between private-sector and publicly listed firms, demonstrating that highly leveraged private firms exhibit greater sensitivity to monetary shocks compared to similarly leveraged public firms. The prevalent firm-specific characteristic that is related to firms' sensitivity to monetary policy in this literature is cash-strappedness and more broadly external financing constraints. In our empirical analysis, we focus on large public firms (albeit with a considerable variation in size across firms) for which these constraints are relatively less binding. Our findings imply that R&D activity has an independent effect on firms' monetary policy sensitivity.

A subset of the literature discussed above examine the relationship between monetary policy and innovation and thus is more closely related to our paper. Grimm et al. (2021), for example, show that expansionary monetary policy, implemented through asset purchase programs, significantly boosts R&D investment. Ma and Zimmermann (2023) uncover a similar procyclicality in R&D and show that monetary tightening reduces innovative activities, including patenting, venture capital investment, and R&D expenditures. Our results also demonstrate the procyclicality of R&D. As mentioned above, however, the focus in our paper is on the effects of R&D intensity on the propagation of monetary policy shocks. We emphasize R&D smoothing behavior of firms and then show and find that this behavior strengthens the transmission of monetary policy shocks.[1]

[1] Our paper is also tangentially linked to the literature that examines a supply-side channel through which monetary policy affects aggregate productivity by influencing resource allocation across heterogeneous firms. Ghassibe (2021),

2 Model

The framework that we follow is a medium scale New Keynesian DSGE model with nominal and real rigidities embedded with an endogenous growth mechanism. The unique components of our model are related to the producers' decision-making and how stochastic growth rate of the economy is incorporated. We, therefore, describe the producers' problem and the link between growth and innovation below, and defer the more standard components of our model to Appendix A.

Intermediate goods in the economy are combined by a representative perfectly competitive firm that uses a constant elasticity of substitution (CES) technology given by,

$$y_t = \left(\int_0^1 \left[y_t(j) \right]^{\frac{\eta_{y,t}-1}{\eta_{y,t}}} dj \right)^{\frac{\eta_{y,t}}{\eta_{y,t}-1}} \tag{1}$$

where y_t and $y_t(j)$ denote the final consumption good and intermediate good j, respectively. $\eta_{y,t}$ regulates the time-variant elasticity of substitution between the intermediate goods. This variable follows an AR(1) process and it captures price mark-up shocks. The profit maximization of the final consumption good aggregator yields the demand condition for intermediate good j.

$$y_t(j) = y_t \left(\frac{P_t(j)}{P_t} \right)^{-\eta_{y,t}} \tag{2}$$

The intermediate goods producers, also indexed by j, are monopolistically competitive. They hire labor services, $l_t(j)$, and rent capital, $k_t(j)$, from households. Each period they distribute labor

for example, provides empirical evidence on the amplification of monetary policy shocks on the real macro variables via production networks. Baqaee et al. (2024) propose a “misallocation channel" showing that monetary expansions reallocate resources towards high-markup firms, boosting productivity and flattening the Phillips curve. Meier and Reinelt (2024) similarly emphasize firm-level heterogeneity but show the opposite effect, finding that tighter monetary policy increases markup dispersion and thus lowers productivity by exacerbating resource misallocation. Gonzalez et al. (2024) shift the focus from markup heterogeneity to capital allocation, demonstrating that monetary expansions alleviate financial frictions, enabling high-productivity firms to invest more, thereby improving capital allocation and total factor productivity. We contribute to this literature by documenting the importance of firm-level heterogeneity in terms of innovation activity as crucial to understanding monetary policy's transmission to the supply side.

services to production activities, $l_t^p(j)$, and R&D activities, $l_t^r(j)$, so that,

$$l_t(j) = l_t^p(j) + l_t^r(j)$$

Firms combine labor and capital to produce intermediate goods according the following Cobb-Douglas function:

$$y_t(j) = z_t\left[u_t(j)\,k_{t-1}(j)\right]^{\alpha}\left[A_t(j)\,l_t^p(j)\right]^{1-\alpha} \tag{3}$$

where z_t is a systematic total factor productivity shock that follows an AR(1) process and α is the income share of capital and $u_t(j)$ is the firm-specific capacity utilization rate. $A_t(j)$ is a crucial component of our analysis here as it represents the effectiveness of production labor that is positively related to R&D activity. This variable is determined as follows:

$$A_t(j) = \left(e^{s_t(j)}\right)^{\eta}(A_t)^{1-\eta} \tag{4}$$

where e is Euler's number. The effectiveness variable depends on both internal and external innovations, $e^{s_t(j)}$ and A_t respectively, with η regulating the relative importance of the two sources. $s_t(j)$ is the stock of innovations for firm j and it evolves according to:

$$s_t(j) = s_{t-1}(j) + v_t l_t^r(j) \tag{5}$$

where v_t represents "stepping on toes effects" and it can also be interpreted as the probability that R&D activity successfully creates an innovation. This variable, hereafter referred to as an "innovation shock", follows an AR(1) process. The external source of efficiency for firm j is the sum of all other firms' efficiencies so that,

$$A_t = \int_0^1 A_t(k)\,dk \quad for \;\; k \neq j \tag{6}$$

Under a symmetric equilibrium A_t also determines the stochastic growth rate of the economy along the balanced growth path as follows:

$$\gamma_t = \frac{A_t}{A_{t-1}} = \frac{e^{s_t}}{e^{s_{t-1}}} = e^{\nu_t l_t^r} \tag{7}$$

When solving the model, we de-trend all growing variables such as output, consumption and capital stock with A_t to ensure stationarity. Therefore de-trended variables such as output, $\widetilde{y}_t$, consumption, $\widetilde{c}_t$, and real wages, $\widetilde{w}_t$, below, represent deviations from the balanced growth path.

$$\widetilde{y}_t = \frac{y_t}{A_t},\ \widetilde{c}_t = \frac{c_t}{A_t},\ \widetilde{w}_t = \frac{W_t/P_t}{A_t} \tag{8}$$

The tildas will be ignored in the rest of the model to simplify notation.

Profits for the intermediate good producer j, $\Pi_t(j)$, is given by,

$$\begin{aligned} \frac{\Pi_t(j)}{P_t} = {} & \frac{P_t(j)}{P_t} y_t(j) - w_t l_t(j) - r_{k,t} k_{t-1}(j) - \frac{\kappa_p}{2}\left(\frac{P_t(j)/P_{t-1}(j)}{\pi_{t-1}^{\varsigma_p}\pi^{1-\varsigma_p}} - 1\right)^2 y_t \\ & - \frac{\kappa_r}{2}\left(\frac{l_t^r(j)}{l_{t-1}^r(j)} - 1\right)^2 w_t l_t^r - \frac{\kappa_u}{1+\varpi}\left[u_t(j)^{1+\varpi} - 1\right] k_{t-1}(j) \end{aligned} \tag{9}$$

where $r_{k,t}$ is the real rental rate of capital and π_t is the inflation rate. The first quadratic cost on the right-hand-side is incurred when adjusting prices, with ς_p and κ_p determining the degree of price indexation and the cost of adjusting prices, respectively.[2] The resulting price stickiness is a feature of our model that is required for monetary policy shocks to be transmitted to the real economy. The second quadratic cost is incurred when adjusting the level of R&D activities. The literature is mixed on the cyclicality of R&D relative to other firm specific expenditures. Some view R&D as a luxury activity that can be dispensed during economic downturns and some attribute a high degree of persistence to R&D citing search and training costs for high-skill labor and the costs of expanding and downsizing R&D infrastructure. In this paper, we are agnostic about these two views and we allow the data to inform us on the value of the parameter κ_r which in turn determines

[2] Following standard practice κ_p is set equal to $(1-\xi_p)\left(1-\xi_p\widetilde{\beta}\right)/3.5\xi_p$, where ξ_p represents the probability of keeping prices the same as the previous period.

the smoothness of R&D relative to other macroeconomic variables. In addition to the two quadratic costs, the firm also incurs capital utilization costs. Parameters ϖ and κ_u determine the elasticity and the level of these costs.

The intermediate good producer's profit maximization problem can be expressed as follows:

$$\max_{k_{t-1}(j),l_t^p(j),l_t^r(j),s_t(j),u_t(j),P_t(j)} E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_{H,t}}{\lambda_{H,0}} \frac{\Pi_t(j)}{P_t} \tag{10}$$

$$\begin{aligned}
&\text{s.t. } \frac{\Pi_t(j)}{P_t} = \frac{P_t(j)}{P_t} y_t(j) - w_t l_t(j) - r_{k,t} k_{t-1}(j) \\
&\frac{\kappa_p}{2}\left(\frac{P_t(j)/P_{t-1}(j)}{\pi_{t-1}^{\varsigma_p}\pi^{1-\varsigma_p}} - 1\right)^2 y_t - \frac{\kappa_r}{2}\left(\frac{l_t^r(j)}{l_{t-1}^r(j)} - 1\right)^2 w_t l_t^r \\
&- \frac{\kappa_u}{1+\varpi}\left[u_t(j)^{1+\varpi} - 1\right] k_{t-1}(j) \\
&\text{s.t. } y_t(j) = z_t \left[u_t(j) k_{t-1}(j)\right]^{\alpha} \left[A_t(j) l_t^p(j)\right]^{1-\alpha} \\
&\text{s.t. } A_t(j) = \left[e^{s_t(j)}\right]^{\eta} A_t^{1-\eta} \\
&\text{s.t. } s_t(j) = s_{t-1}(j) + \nu_t l_t^r(j) \\
&\text{s.t. } y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\eta_{y,t}} y_t \\
&\text{s.t. } l_t(j) = l_t^p(j) + l_t^r(j)
\end{aligned}$$

The maximization problem with respect to capital stock, production labor, R&D activities, knowledge stock and prices produce the optimality conditions below. For each condition, we also include its log-linearized form under a symmetric equilibrium (symmetry across all agents).

Capital:

$$\Omega_t \alpha \frac{y_t(j)}{k_{t-1}(j)} = r_{k,t} \tag{11}$$

$$\widehat{\Omega}_t + \widehat{y}_t - \left(\widehat{k}_{t-1} - \widehat{\gamma}_t\right) = \widehat{r}_{k,t} \tag{12}$$

Production labor:

$$(1-\alpha)\Omega_t \frac{(P_t(j)/P_t) y_t(j)}{l_t^p(j)} = w_t \tag{13}$$

$$\widehat{\Omega}_t + \widehat{y}_t - \widehat{l}_t^p = \widehat{w}_t \tag{14}$$

R&D:

$$\left[1 + \kappa_H \left(\frac{l_t^r}{l_{t-1}^r} - 1\right) \frac{l_t^r}{l_{t-1}^r}\right] w_t = A_t \mu_t \nu_t + \kappa_r E_t \left[\left(\beta \frac{\lambda_{H,t+1}}{\lambda_{H,t}}\right) \left(\frac{l_{t+1}^r}{l_t^r} - 1\right) \left(\frac{l_{t+1}^r}{l_t^r}\right)^2 w_{t+1}\right] \tag{15}$$

$$\widehat{w}_t + \kappa_H \left(\widehat{l}_t^r - \widehat{l}_{t-1}^r\right) = \widehat{\mu}_t + \widehat{\nu}_t + \kappa_r \left(\widehat{l}_{t+1}^r - \widehat{l}_t^r\right) \tag{16}$$

Knowledge stock:

$$\mu_t = E_t \left[\left(\beta \frac{\lambda_{H,t+1}}{\lambda_{H,t}}\right) \gamma_{t+1} \mu_{t+1}\right] + \Omega_t (1-\alpha) \left(\frac{y_t(j)}{A_t(j)}\right) \eta \tag{17}$$

$$\widehat{\mu}_t = \beta E_t \left[\widehat{\mu}_{t+1} + \widehat{\gamma}_{t+1} - \left(\widehat{R}_t - E_t \widehat{\pi}_{t+1} + \widehat{\phi}_t\right)\right] + (1-\beta) \left(\widehat{w}_t + \widehat{l}_t^p\right) \tag{18}$$

μ_t here is the marginal benefit of R&D services and it is captured by the Lagrange multiplier on the evolution of knowledge stock. The marginal benefit of a unit of R&D activity today includes the efficiency gains and profits both today and in future periods through changes in the stock of knowledge. Ω_t is Lagrange multiplier corresponding to the production function.

Prices:

$$\begin{aligned} &\left(\frac{\pi_t}{\pi_{t-1}^{\varsigma_p} \pi^{1-\varsigma_p}} - 1\right) \frac{\pi_t}{\pi_{t-1}^{\varsigma_p} \pi^{1-\varsigma_p}} \\ &= E_t \left[\left(\beta \frac{l_{t+1}^r}{l_t^r}\right) \left(\frac{\pi_{t+1}}{\pi_t^{\varsigma_p} \pi^{1-\varsigma_p}} - 1\right) \frac{\pi_{t+1}}{\pi_t^{\varsigma_p} \pi^{1-\varsigma_p}} \frac{y_{t+1}}{y_t}\right] - \frac{\eta_{y,t} - 1}{\kappa_p} (1 - \Omega_t \theta_{p,t}) \end{aligned} \tag{19}$$

$$\widehat{\pi}_t = \frac{\varsigma_p}{1+\beta\varsigma_p} \widehat{\pi}_{t-1} + \frac{\beta}{1+\beta\varsigma_p} E_t \widehat{\pi}_{t+1} + \frac{\eta_y - 1}{(1+\beta\varsigma_p)\kappa_p} \left[\widehat{w}_t - \left(\widehat{y}_t - \widehat{l}_t^p\right) + \widehat{\theta}_{p,t}\right] \tag{20}$$

where $\theta_{p,t} = \frac{\eta_{y,t}}{\eta_{y,t}-1}$.

Capacity utilization:

$$\Omega_t \alpha \frac{y_t(j)}{u_t(j)} = \kappa_u u_t(j)^{\varpi} k_{t-1}(j) \tag{21}$$

The central focus of our paper is on monetary transmission. Monetary policy instrument in the economy is the risk-free interest rate that is regulated by the central bank according to the following Taylor rule:

$$R_t = (R_{t-1})^{\rho} \left[R\,(\pi_t/\pi)^{\alpha_\pi} (y_t/A_t y)^{\alpha_y} \right]^{1-\rho} \widetilde{\varepsilon}_{R,t} \tag{22}$$

where parameters ρ, α_π, and α_y are the interest rate smoothing term and the weights of inflation and output gap, respectively, and R and y are the risk-free interest rate and the de-trended level of output at steady state. $\widetilde{\varepsilon}_{R,t}$ represents a monetary policy shock that follows an AR(1) process.

Log-linearizing the Taylor rule yields the following condition:

$$\widehat{R}_t = \rho \widehat{R}_{t-1} + (1-\rho)\left[\alpha_\pi \widehat{\pi}_t + \alpha_y \widehat{y}_t\right] + \widetilde{\varepsilon}_{R,t} \tag{23}$$

3 Estimation

To assess the impact of R&D for monetary transmission we estimate our baseline model by following several steps. Before estimating the model, we de-trend all growing variables with the stochastic labor efficiency term to ensure stationarity. We then log-linearize all model equations so that variables represent deviations from their balanced growth path.

Next, we use a Bayesian methodology to estimate the structural and shock parameters of the model. To do so, the model's state space representation is first converted to its reduced form state (similar to Blanchard and Khan, 1980) to identify orthogonal shocks. The predetermined variables are then linked to the observed variables via measurement equations. These variables, together with the prior distributions of the parameter values, are incorporated into a likelihood function via a Kalman filter. This likelihood function is multiplied by the parameters' prior distributions to obtain a posterior density function. Finally, the posterior density function is maximized to obtain optimal posterior parameter distributions by using a Markov Chain Monte Carlo simulation.

In addition to the 4 shocks mentioned in the previous section, (monetary policy, price mark-up and total factor productivity and innovation shocks), the full model includes investment, government spending, cost of capital and wage mark-up shocks. While Appendix A demonstrates how these shocks are incorporated into the model, it is useful at this point to describe the four other shocks as they are important for estimating the model and thus identifying the independent effects of monetary policy shocks on the economy. Investment shock represents an exogenous change to the investment-specific technology that converts investment to capital. This shock, therefore, is introduced through the capital accumulation equation and its positive values imply a larger amount of new capital for a unit of investment and thus higher returns to capital and investment demand. The government expenditure shock enters the resource constraint of the economy and its positive values represent a discretionary fiscal expansion that in turn crowds out other demand components. The cost of capital shock captures exogenous changes in credit spreads, that is commonly interpreted as a systematic change in the volatility of idiosyncratic shocks that capital owners face. Finally, the model features a wage mark-up shock that generates a wedge between wages and the marginal rate of substitution between labor services.

We use 8 quarterly US data series, spanning the time period 2006Q2 to 2023Q4, to match the 8 shocks mentioned above in estimating the model.[3] From the Federal Reserve Bank of St. Louis, FRED, database, we collect the real gross private domestic investment, real gross domestic product, real government consumption expenditures and gross Investment, gross domestic product implicit price deflator. For the policy rate, we use the Wu-Xia shadow rate.[4] The two remaining series are obtained from the Bureau of Labor Statistics (BLS) database. The aggregate weekly hours of all employees (total private) and those engaging in scientific research and development services are used to capture total labor and R&D services, respectively.[5] All data series are seasonally adjusted and they are demeaned prior to estimation. The series are also transformed to reflect quarterly growth rates, with the exception of the shadow rate that is included in levels. We should also note that the stochastic growth rate is accounted for when linking the de-trended model variables to the series mentioned above in the observation equations.

[3]The R&D series that we use is available starting 2006Q2. This is why 2006Q2 is the starting point.
[4]The shadow rate series is obtained from Jing Cynthia Wu's website.
[5]The BLS codes for the two series are CES0500000056 and CES6054170056, respectively.

The prior distributions of the parameters are fairly similar to those in the literature (Smets and Wouters, 2007 and Gilchrist et al., 2009) and they are consistent with macro-econometric findings. The description of these parameters, their prior distributions and the posterior estimates are deferred to Appendix B. The model also includes level parameters that can be obtained from the steady state conditions of the model and thus are not estimated. These parameters are also fairly standard and they are discussed in Appendix B. It is however useful at this point to mention how we determine the level parameters that govern the non-standard components of the model.

First, to match the annual trend growth rate of the economy over the 1990:Q2 to 2023:Q4 time period, we set γ equal to 1.005. Second, we set the share of R&D services in total labor services, l_t^r, to 3%. This ratio roughly represents the average share of scientists and engineers employed for R&D activities in total employment between 2000 and 2020 in National Science Foundation's Business R&D and Innovation Surveys (BRDIS) and Business Enterprise Research and Development (BERD) surveys. This share rises to 8% Chemicals, Transportation, Information, Professional, scientific and technical services, Computer and electronics sectors. The 3% share that we use is a reasonable baseline value given that scientists and engineers are not the only types of labor employed for R&D.[6] These two data moments imply that the externality and stepping on toes parameters η and ν, are equal to 0.358 and 0.005, respectively. The value for η is reasonably similar to its estimated value of 0.28 in Bianchi et al. (2019). The stepping on toes parameter value implies that the annual success rate of innovation is 2 percent. This is lower than the estimates (as low as 4.5 percent) in the literature that predates the Great Recession (Vangundy, 2007; Cooper, 1983; Cozijnsen et al., 2000). With higher GDP growth rate, our hazard rate is more aligned with empirical evidence.

Appendix B describes the steady state of our model and how we pin down the non-standard parameters in the model.

[6]The share of R&D spending to GDP ratio in the past 35 years is also roughly 2%.

3.1 Results

Figure 1 displays the responses (deviations from the balanced growth path) to a one standard deviation shock to the shadow rate. The monetary tightening generates a fall in output and inflation, and a relatively smaller response in consumption due to habit persistence. The focal point of our analysis is on R&D and the innovation process. As displayed in the figure, we observe a sharper drop in the marginal benefits of R&D relative to the marginal benefits of production services.

The reason for the disparity described above is that while there are diminishing marginal benefits/returns to production labor, the marginal returns to R&D is proportional to output in the model. The drop in production labor generated by the adverse shock counteracts the drop in production, this counteractive force is not observed for R&D. In other words, the marginal benefits of R&D are not higher at lower levels of R&D. The relatively higher responsiveness of the marginal benefits to R&D implies that a smaller response of R&D is sufficient to match the marginal returns to production labor. There are three other reasons why the magnitude of the R&D response is smaller. First, adjustment costs incurred when curbing R&D activities forms a wedge between the marginal costs and benefits to R&D and prompts a smaller response in R&D. Second, the drop in R&D decreases labor efficiency not only in the current period but also in future periods, amplifying the costs of changing the level of R&D. This intertemporal propagation of R&D benefits is also the reason why the R&D response is more persistent compared to production services. Finally, due to the response of real interest rates to monetary policy future benefits of R&D are discounted at a lower rate during a monetary expansion and at a higher rate during a monetary tightening. This amplifies the response of the marginal benefits to R&D and mitigates the R&D response similar to the channels described above.

Next, we report and investigate the historical decomposition of output in the estimated model. These decompositions, illustrated in Figure 2, quantify the contribution of specific shock in a given period, and its lagged values, to the deviation of an endogenous variable from its value along the balanced growth path for each ensuing period. To simplify the illustration, we classify government spending, investment, and cost of capital shocks under the demand/financial shocks category and wage and price mark-up shocks under the price shocks category. The decompositions indicate that the total factor productivity, demand/financial and price shocks are equally important drivers of output during the period before the pandemic, with monetary policy shocks playing a lesser role. Monetary policy shocks make a large contribution to output variation following the pandemic, demonstrating the "lean against the wind" policies during this period.

A more central observation for our analysis is that innovation shocks make a relatively minor contribution to the variation of output. While this evidence indicates that R&D driven shifts in efficiency are trivial for business cycles, it does not necessarily imply that the endogenous growth mechanism in the model is inconsequential. When we shut this mechanism off and estimate a standard medium-scale dynamic new Keynesian model (leaving out R&D services from the set of observable variables), we observe, in Figure 3, a more muted output response to a monetary policy shock and we detect, in Figure 4, a much smaller contribution of demand/financial shocks to output variation. Compared to the baseline estimation, the contributions of demand/financial shocks to output volatility are distributed to price and total factor productivity (TFP) shocks.

These results suggest that while unanticipated changes in innovation do not drive business cycles, the innovation process forms an effective conduit for the transmission of demand and financial shocks to the economy. This transmission is explained by firms' R&D smoothing behavior. Firms' decision to keep R&D relatively stable, and consequently the sharper changes in production services and output, allow the estimated model to match the changes in demand generated by government spending, investment and cost of capital shocks. Without this endogenous mechanism, part of the wedge between output and spending is absorbed by price and TFP shocks.

3.2 Heterogenous firms

So far we assumed that each firm engages in R&D and that they are symmetric. In this section, we forgo this assumption and distinguish between firms that conduct R&D and those that do not to determine how shock transmission operates through the two types of firms. This variation also allows us to form a closer link with the second half of the paper where we empirically compare the transmission of monetary policy shocks across firms with different degrees of R&D spending.

To extend the model, we assume that there are two broad types of intermediate goods, those produced by the firms with R&D activity described above (hereafter, creators), and those that adopt the technologies created by the firms engaging in R&D activity (hereafter, adopters). The adopters are also monopolistically competitive and they produce output according to the following function:

$$y_{a,t}(m) = z_t \left[k_{a,t-1}(m)\right]^{\alpha} \left[A_t l^{p}_{a,t}(m)\right]^{1-\alpha} \tag{24}$$

where m indexes the adopters. The production functions of the two types of firms, adopters and creators, are similar, featuring the same TFP shock and the same income share parameter. There are, however, two differences. First, the adopters do not choose the level of labor efficiency, A_t, and simply adopt the new technologies of the creators. Second, the market for adopters is more competitive with lower mark-ups. The second assumption allows us to implicitly incorporate the well-documented positive link between R&D activity and mark-ups (c.f., Aghion and Howitt, 1992).

The adopters' aggregate output is composed of firm-specific output according to

$$y_{a,t} = \left(\int_0^1 \left[y_{a,t}(m)\right]^{\frac{\eta_{a,t}-1}{\eta_{a,t}}} dm\right)^{\frac{\eta_{a,t}}{\eta_{a,t}-1}} \tag{25}$$

where $\eta_{a,t}$ denotes the time-varying elasticity of substitution (with $\eta_{c,t}$ denoting the corresponding variable for the creators). We assume that capital stock, labor demand, price of capital and returns to capital are type specific. Due to arbitrage, however, the expected returns to capital are the same for each type of firm. The maximization problem of the adopters is similar to that of the creators except R&D activity is not a decision variable for these agents.

The two types of intermediate goods are combined to produce wholesale output as follows:

$$y_t = \left[\lambda_c^{\frac{1}{\eta_{w,t}}} \left(y_{c,t}\right)^{\frac{\eta_{w,t}-1}{\eta_{w,t}}} + (1-\lambda_c)^{\frac{1}{\eta_{w,t}}} \left(y_{a,t}\right)^{\frac{\eta_{w,t}-1}{\eta_{w,t}}}\right]^{\frac{\eta_{w,t}}{\eta_{w,t}-1}} \tag{26}$$

where $y_{c,t}$ is the aggregate output of the creators, $\eta_{w,t}$ is the elasticity of substitution between the two types of intermediate goods, and λ_c governs the share of intermediate goods produced by the creators in the aggregate wholesale output.

The corresponding aggregate price index is given by,

$$P_t = \left[\lambda_c P_{c,t}^{1-\eta_{w,t}} + (1-\lambda_c) P_{a,t}^{1-\eta_{w,t}}\right]^{1/(1-\eta_{w,t})} \tag{27}$$

where the relative prices of the two goods can be expressed as follows:

$$\frac{P_{c,t}}{P_t} = \lambda_c^{1/\eta_{w,t}} \left(\frac{y_{c,t}}{y_t}\right)^{-1/\eta_{w,t}} \quad , \quad \frac{P_{a,t}}{P_t} = (1-\lambda_c)^{1/\eta_{w,t}} \left(\frac{y_{a,t}}{y_t}\right)^{-1/\eta_{w,t}} \tag{28}$$

The aggregate price index after first-differencing can be written in log-linearized form as,

$$\pi_t = \lambda_c \pi_{c,t} + (1-\lambda_c) \pi_{a,t} \tag{29}$$

The additional level parameter in this section is λ_c. To fix this parameter, we use our firm level COMPUSTAT data set, described in greater detail below. In this data set, total sales of firms that do not report any R&D expense is on average 74.1% of total sales by all firms. Adding firms with R&D expenditures less than 5% of total sales increases the ratio to roughly 90%, implying a value of 0.1 for λ_c. To compute the latter ratio, we first measure the total sales of firms with R&D expenditures less than 5% of their total sales in each quarter and calculate the ratio of these sales to total sales by all firms in that quarter. We then compute the average value of this ratio across all quarters in the sample. We use the 5% cutoff to more clearly distinguish between firms that do and do not conduct substantial R&D activity.[7]

We use the same methodology to obtain the growth rates of quarterly sales for firms that do and do not report R&D activity. We then adjust the two data series for inflation and feed them into our estimation, replacing total output growth, as the two additional observables.

[7]We obtain qualitatively similar estimation results when we use a smaller value for λ_c.

3.2.1 Results

Before discussing the estimation results, we first describe the output responses to a monetary policy shock under different calibrations of the model. The responses, displayed in Figure 5, are obtained by using the level parameters and the prior mean values of the estimated parameters described in Appendix B. It should be noted that we set the elasticity of substitution between the two types of output to 1 in our baseline calibrations. While there is no empirical evidence that exactly matches the two types of intermediate goods in our model, empirical estimates for different types of consumption goods typically ranges between 0.5 and 2 and thus fixing η_w to 1 is a reasonable approach for our baseline simulations. We do also conduct a sensitivity analysis with different values as discussed below.

Consistent with earlier results, we find that the output of creators, the R&D conducting firms, is much more responsive to a monetary policy shock under each calibration as displayed in Figure 5. The mechanism here is similar. Creators' output is more sensitive to the changes in demand generated by a monetary policy shock due to high adjustment costs and marginal returns associated with R&D activity.

In our baseline model, we assume that firms do not incur any cost of adopting technologies. If we assume instead that adopters lose χ^a units of output for every unit of A_t that they obtain from creators, we find that the magnitude of the negative response of the creators' output to monetary policy shocks is smaller. Fixing χ^a so that adoption costs are 3% of output, within the range of values in empirical findings (see, Bessen, 2002), however, we observe a modest drop in the magnitude of the response. We make a similar observation when we set the output share of creators to a higher value. Setting λ_c equal to 0.2, produces a quantitatively similar disparity between the output responses of the two firms.

Increasing the elasticity of substitution and the steady state share of R&D in the creators' labor services amplifies the negative response of creators' output to a monetary tightening. With higher elasticity of substitution, there is sharper drop in the price of creators' output since their goods are more substitutable. The latter result implies that R&D intensity within firms reinforces the amplification mechanism in our model. This positive relationship is related to the sensitivity of R&D to the changes in demand. When R&D services' share is high at steady state, it becomes more sensitive to the changes in demand since smaller changes in R&D are sufficient to restore the disparity between the marginal benefits of R&D and production labor services. The decline in demand due to the adverse monetary policy shock, therefore, generates a smaller response in R&D and a larger negative response in production labor and output. Finally, we observe a positive relationship between the creators' market power and their responsiveness to monetary policy shocks. This observation is consistent with empirical findings (c.f., De Loecker and Eeckhout, 2020; Duval et al., 2024) and it is due to the negative relationship between market power and the elasticity of demand.

We proceed by estimating the model with the two types of firms. As mentioned, we use the sales growth for high and low R&D firms instead of total output as observable variables in doing so. The contributions of monetary policy shocks to the variation in output growth rates displayed in Figure 6 reveal, consistent with earlier inferences, that monetary transmission through high-R&D firms has been much stronger. Also similar to earlier results, we observe, in Figure 7, a more substantial contribution of demand/financial shocks to the variation in creators' output.

4 Empirical Analysis

In this section, we use empirical analyses to determine whether the positive relationship between R&D intensity and the strength of monetary policy transmission in our model is supported by firm-level data. We first measure and compare firms' sensitivity to monetary policy shocks. We then use a two methodologies to identify the unique contribution of R&D activity to the said sensitivity.

4.1 Evidence from firm-level sales data

We begin by determining how the response of firms' output to monetary policy shocks varies with their R&D intensity. To do so, we approximate firms' output groth with their real sales growth rates, $s^g_{i,t}$, and conform to standard practice in the monetary transmission literature (Gertler and Gilchrist, 1994; Cetorelli and Goldberg, 2012; Kashyap and Stein, 2000) and use 8 quarterly lags of a monetary policy measure, mps_t, in the following dynamic panel model:

$$
\begin{aligned}
s^g_{i,t} = & \sum_{k=1}^{8} \alpha_k s^g_{i,t-k} + \sum_{k=1}^{8} \beta_k mps_{t-k} + \gamma rd_{i,t-1} + \sum_{k=1}^{8} \lambda_k \left(rd_{i,t-1} * mps_{t-k} \right) \\
& + \sum_{x \in Control} \sum_{k=1}^{8} \eta_{x,k} \left(x_{i,t-1} * mps_{t-k} \right) + \sum_{x \in Control} \mu_x x_{i,t-1} + \varepsilon_{i,t}
\end{aligned}
\tag{30}
$$

where subscripts i and t index firms and the quarter, respectively. $rd_{i,t-1}$ is our measure of R&D intensity and it is measured as the ratio of firms' R&D investment spending to their total assets. mps_t is a monetary shock series (described below). A positive shock reflects a monetary tightening. The focus of our estimations is on the interaction of this variable with R&D intensity. In particular, if the estimated values of β_k and λ_k are both negative on aggregate, this would imply that R&D intensity amplifies the responses to monetary policy shocks and that the predictions of our DSGE model are supported by firm-level data. Equation (30) will generate unbiased estimates under the assumption that the correlation between the error term, $\varepsilon_{i,t}$, and monetary policy shocks is not systematically related to the R&D intensity of firms. To reduce the omitted variable bias concerns, we include a set of control variables, $x_{i,t-1}$, and their interaction with the monetary policy shock. The control variables that we include, firms' leverage (long-term debt plus short-term debt / assets), liquidity (cash flow / assets) and profitability (Tobin's Q), are commonly used in studies that investigate the transmission of monetary policy through firms and they are often significantly related to firms' R&D investment in empirical findings.[8] We should also mention here that the form of the control variables and their interaction with the monetary policy shock series is more broadly similar to the specification in Gomez et al. (2021) who study the interaction of monetary policy shocks with maturity mismatches.

To estimate the dynamic panel model above, we use the Blundell and Bond (1998) system general method of moments (GMM) estimator. This estimator is designed to address endogeneity

[8] Tobin's Q is measured as number of common shares times their closing price divided by total assets.

issues that arise from models that have lagged values of the dependent variable on the right hand side, in particular those with large cross-section and small time dimensions, and it accounts for unobserved fixed effects.

Our data are primarily obtained from two sources and they cover the 2000 to 2023 time period. Table C.1 in Appendix C provides a detailed description of the data and the sources. The monetary policy shock series, obtained from Bu et al. (2021), captures shocks to US monetary policy under both conventional and unconventional policymaking while remaining largely free from the central bank's information effect. These data are available at the monthly frequency. The firm-level data are from the COMPUSTAT North America database and they are at the quarterly frequency. To match the frequencies between the two, we follow common practice and construct a 3-month moving sum series of the monetary policy shock (e.g., Durante et al., 2022). Our sample is restricted to nonfinancial private firms that are headquartered in the U.S., and those that report positive sales and assets. All financial variables are converted to real terms using the GDP deflator.

In addition to using the whole sample to estimate equation (30), in each quarter, we restrict the sample to firms that report positive R&D spending and separate these firms into two groups, high and low R&D firms, to determine whether the relationship between monetary policy transmission and R&D spending is different across the two groups. In these exercises, the high and low R&D samples consists of firms with R&D expenditures in the top 40^{th} and bottom 40^{th} percentiles in a given year and quarter, respectively.

Statistics reported in Table 1 indicate that firms with R&D activity report faster sales growth, lower financial leverage, higher liquidity, and lower market to book value compared to the firms without R&D activity. R&D expenditures as a fraction of assets is roughly 2.3%. Consistent with the DSGE model, we observe that the Herfindahl-Hirschman index is considerably larger for the R&D group suggesting a higher degree of concentration amongst firms that engage in R&D activity.[9] Notice however that the higher concentration ratio does not imply that the R&D firms

[9] We calculate this statistic by measuring the Herfindahl-Hirschman index for each quarter and then taking the average of these quarterly values across the sample period. We do this separately for each group of firms.

are larger as the average assets for the two groups is similar.[10] One advantage of our analysis is that it uses a vast amount of observations to draw inferences, especially along the cross-section dimension of our sample.

4.1.1 Results

We begin by estimating equation (30) for the whole sample and for the two groups of firms mentioned above. For the latter estimations, we use two specifications, one with R&D expenditures and one without. We do so to compare the magnitude and the significance of the monetary policy shock coefficient across the two groups by using a common specification.

The results in column 1 of Table 2 indicate that a monetary tightening is negatively related to sales growth for the whole sample. The standard deviation of the monetary shock variable that we use is equal to 0.387 in our sample period. The coefficient value of -0.0895 in column 1 then implies that in a given quarter firms' sales growth rate decreases by 0.433 percentage points in response to a positive one-standard-deviation monetary policy shock, evenly distributed across the previous 8 quarters (a 0.125 standard deviation increase per quarter). This sensitivity is economically large given that the average quarterly sales growth in our sample is roughly 0.5 percent.

Consistent with the descriptive statistics we observe that R&D activity is positively related to sales growth, a one percentage point increase in R&D to total assets ratio corresponding to a 2.43 percentage point faster sales growth. The more critical finding for our analysis is that R&D activity amplifies the responses to monetary policy shocks. Specifically the negative value of the interactive term with R&D and monetary policy shock suggests that a monetary tightening is more negatively related to sales growth for firms with a high level of R&D spending. The interactive variable coefficient value implies that the sales growth of a firm with a R&D to total assets ratio of 1 percent is roughly 2.5 times more sensitive to monetary policy compared to a firm that does not engage in R&D.[11] The corresponding value in column 2 indicates that this impact of R&D

[10] We similarly compute the mean value of total assets in each quarter and then take the averages of these values across the sample period. To do so, we measure assets in millions of chained 2017 US dollars.

[11] In the sample, the R&D to assets ratio for the 25^{th}, 50^{th} and 75^{th} percentiles are 0, 0.97 and 2.39 percent, respectively. The interactive variable coefficient value implies that the real sales growth of a firm with median R&D to

expenditures is higher when the sample is restricted to firms that report R&D spending.

Next, we omit R&D spending from equation (30) to compare two groups' sensitivity to monetary policy. The results reported in the last two columns show that the sales growth of only R&D firms is negatively and significantly related to monetary policy shocks. This inference is consistent with our DSGE model results and it suggests that monetary transmission operates more strongly through firms that engage in R&D activity. The results also indicate that more liquid firms report faster lending growth during a monetary tightening and that overvalued firms generally report faster lending growth.

Large monetary policy shocks There is a growing literature on the nonlinearities in monetary policy shock transmission. Studies such as Fasani et al. (2024), Debortoli et al. (2020), Gagnon et al. (2011) and Anzuini (2021) in particular find, mostly using a Treshold VAR analysis, that the impact of monetary policy shocks on the economy may not be proportional to the size of the shock, with larger shocks having a greater impact. We proceed by re-estimating our model by omitting smaller monetary policy shocks. To do so, we only keep shocks that are at least 1/3 standard deviations away from the mean value.

Results displayed in Table 3, consistent with the aforementioned literature, indicate a stronger transmission. Specifically, under each specification the coefficients of both the monetary policy shock and its interaction with R&D are larger in magnitude compared to the baseline results. With large shocks, the sales growth of firms without any R&D expenditures is still not significantly responsive to monetary policy shocks. We should also mention that we drew similar inferences from estimations with more common measures of monetary policy stance. The results that we obtained by using the federal funds rate, for example, similarly suggest a higher monetary policy sensitivity for firms with R&D expenditures.[12].

assets ratio will be -0.95 percentage point lower compared to a firm that does not engage in R&D. This effect is -2.35 percentage points for the firm at the 75^{th} percentile.

[12] We obtained similar results by using the Wi-Xia shadow rate. The results are available upon request.

Evidence from subsamples In this section, we distinguish between firms with high and low R&D expenditures and those that are large and small. Throughout the estimations, we use the specification without the interactive terms since R&D to total assets ratios is very small for low R&D firms.

Our baseline sample with R&D includes a considerable number of observations with a negligible amount of R&D expenditures, especially when compared to the size of the firms. In an alternative estimation, we omit observations with a R&D-to-assets ratio less than 0.05 percent to more clearly distinguish between firms that engage in a significant amount of R&D activity and those that do not.[13] The results displayed in column 2 of Table 4 indicate a stronger transmission of monetary policy to the sales growth of firms with a significant amount of R&D.

As we mentioned in our description of the data above, the differences in the size of firms with and without R&D are small on average. Nevertheless, to further ascertain that our results are driven by R&D intensity and not size effects, we distinguish between and large and small firms in our estimations. In doing so, we also split the sample into high and low R&D groups to more clearly identify the contribution of R&D to monetary policy sensitivity so that we form four subsamples: high R&D, high assets; high R&D, low assets; low R&D, high assets; low R&D, low assets. We make these categorizations in each quarter and allocate firms top (bottom) 40^{th} percentile of the asset distribution in a given quarter to the high (low) assets in that quarter. We use R&D-to-total-assets ratio and the same thresholds for the high and low R&D classification. For the latter group, however, we also include firms without any R&D expenditures. The results corresponding to the subsamples are reported in the last 4 columns of Table 4. Consistent with our earlier inferences, we observe a higher monetary policy sensitivity for high R&D firms. For these firms, the differences in size does not appear to be a significant determinant of the said sensitivity. We do, however, find that amongst firms with low or no R&D expenditures, those that are smaller are more sensitive to monetary policy shocks. The latter result is consistent with the common finding that smaller firms are more cash-strapped and external finance dependent and thus more

[13] We used alternative threshold values and obtained quantitatively and qualitatively similar results.

responsive to monetary policy shocks that impact their funding costs.

While these results suggest that the higher monetary policy sensitivity of R&D intensive firms may not be related to their size, below we perform an alternative analysis to determine the unique contribution of R&D to the monetary policy sensitivity of sales growth.

A propensity score matching exercise In this section, we take a different approach to analyzing the sensitivity of firm's sales to the monetary policy shocks without assuming a specific functional relationship between the monetary policy shocks, firm-level financial variables and the sales growth rates. We use a propensity score matching method which mimics randomization. To examine the effect of monetary policy on firms' output, we first estimate the following equation separately for each firm to determine the sensitivity of firms' sales to monetary policy shocks:

$$s^g_{i,t} = \alpha^{ps}_i + \sum_{k=0}^{8} \beta^{ps}_{i,k} mps_{t-k} + \varepsilon_{i,t} \tag{31}$$

where $s^g_{i,t}$ similarly denotes the quarterly sales growth of firm i in quarter t. To estimate equation (31), we use OLS method with robust standard errors. Since this estimation is repeated at the firm level, it is important to have some continuity in the number of observations for each firm. To increase the strength of the estimation, we focus on firms that have at least 15 observations in our sample, which means we drop the lowest 5th percentile in terms of observation counts. After obtaining all the estimates, we keep firms with beta estimates that are jointly significant at the 10 percent level or lower. For these firms, the sensitivity of sales to monetary policy shocks is calculated as $smp_i = \sum_{k=0}^{8} \hat{\beta}^{ps}_{i,k}$.

The first step described above transforms the dataset into a cross-sectional structure where each firm has a single estimate of sales sensitivity to shocks. As a second step, we use smp_i as the outcome variable in our propensity score matching exercise. Our treatment variable, High R&D, is assigned the value of 1 if a firm's average R&D-to-asset ratio during the whole sample period exceeds a certain percentile of the sample, and 0 otherwise. In an alternative estimations, we use the low R&D observations (R&D to total asset ratios below specific threshold values) to construct our treatment variable. In this second stage, we include firms' size, liquidity (cash flow / assets), leverage, and Tobin's Q ratios (also measured as values across the whole sample period) as covariates for estimating the treatment effects. of R&D intensity.

The top three rows of Table 5 presents the average treatment effects for estimations that use the high R&D criterion to construct the treatment variable. The results in rows 1, 2 and 3 correspond to the treatment groups with R&D ratios in the top 60^{th} and 70^{th} percentiles and those with positive R&D expenditures, respectively. The coefficient value of -0.0496 suggests that the average negative sensitivity of sales growth to monetary policy shocks would be roughly 5 percentage points higher in absolute value if a firm with low R&D transitions to the high R&D group. The magnitude of this coefficient is considerably large given that the average sensitivity to monetary policy in our estimations is roughly -0.09. We detect a similar reinforcement mechanism when we use alternative definitions of high R&D. By contrast, when we construct our binary treatment variable by assigning the value of 1 to observations below the bottom 30^{th} and 40^{th} percentile of the RD-to-total-assets ratio we find a mitigating treatment effect as displayed in the bottom two rows of Table 5. Specifically, the positive and significant coefficient values in these rows imply that having lower R&D mitigates the responsiveness of sales growth to monetary policy shocks.

Overall, the results from our proposensity score matching exercise, consistent with our baseline panel estimations, suggest that monetary policy shocks have a more negative impact on the sales growth of firms that have higher R&D-to-assets ratios but are similar otherwise.

4.2 Evidence from higher frequency data

Our empirical analysis and the estimated DSGE model revealed a stronger transmission of shocks through high R&D firms at the quarterly frequency. In this section, we use daily data to test whether the mechanisms that we identify also describe the short-run transmission of shocks.

To conduct this test we change our analysis in two main ways. First, we replace sales with the daily observations for firms' closing stock prices as sales growth data are not available at the daily frequency. Second, we replace the monetary shock series in our baseline analysis with the Kim and Wright (2005) term premium shock series. This shock series, available at the daily frequency, is obtained from a three factor model and that reflects the unanticipated changes in the spread between the yields of 10-year US Treasury bonds and 3 month US Treasury bills. While term premium shocks are related to many factors, including changes in risk perception, there is a strong connection with term premium shocks and monetary policy in the literature (e.g., Gomez et al., 2021; Paul, 2023) and using this measure, therefore, is a natural choice for restructuring our analysis. To further strengthen the link between monetary policy shocks, we focus on the days of Federal Open Market Committee (FOMC) announcements only, with the identifying assumption that monetary policy news dominates the market on these days.

The model that we estimate is as follows:

$$
\begin{aligned}
r_{i,t} = {} & \alpha_i^s + \beta_i^s tp_t + \gamma_i^s rd_{i,t-n(t)} + \lambda_i^s rd_{i,t-n(t)} * tp_t + \Lambda_i C_{i,t-n(t)} \\
& + \eta_i^s r_t^{3m} + \mu_i^s \left[E(h_t) - r_t^{3m} \right] + \varepsilon_{i,t}^s
\end{aligned} \tag{32}
$$

where $r_{i,t}$ is the daily stock price of firm i, tp_t is the Kim and Wright (2005) term premium shock. Since the financial ratios and expenditures are only available at the quarterly frequency, we use the latest quarterly observation for these firm-specific variables that are available at date t. We similarly capture R&D intensity, $rd_{i,t-n(t)}$, by using the R&D-to-total-assets ratio and use the same ratios, included in the vector $C_{i,t-n(t)}$ above, to capture the profitability, liquidity and profitability of a firm. The last two terms in the equation above capture the level and expected slope shifts of the yield curve and allows us to distinguish between the expected path of the term premium variable and term premium shocks. Here $E(h_t)$ is the daily change in the average expected future 3 month T-bill rates over the maturity horizon of the Treasury bond and r_t^{3m} is the daily change in the yield of a 3 month T-bill at time t.

To construct our data set we first obtain the Kim and Wright (2015) data series, the term premium shock and the expected term premium, and the 3-month T-bill data are obtained from FRED. Next, we collect daily stock price data for all the firms and the sample period in our baseline analysis from the CRSP/COMPUSTAT Merged Database. Finally, we add firms' quarterly financial ratios and R&D-to-total-assets ratio as described above. To maintain consistency with our baseline analysis, we focus on firms headquartered in the US, we exclude firms with negative sales, nonpositive assets and negative R&D expenditures. All firm level data obtained from CRSP/COMPUSTAT Merged Database are deflated using the GDP deflator (indexed to 2017) and winsorized at 1 percent. Our final sample consists of 18,745 firms with around 1.1 million observations.

We estimate equation (32) by using a fixed-effects estimator with standard errors clustered by firm. We choose to do so since it is the more standard approach when the lags of the dependent variable are not included on the right-hand-side. The results obtained from the estimation of equation (32) are displayed in Table 6. There are two central results. First, we find that firms' stock prices are negatively related to the term premium shock. This result is consistent with a reallocation of funds to safer assets and a decrease in the demand for equity in response to an unanticipated increase in long-term risk. More critical for our paper, we find that R&D intensity mitigates this response of stock prices. Specifically, stock returns for firms with higher R&D activity are less responsive to term premium shocks. This result presents a contrast to the main inference that we drew from quarterly data. While a more rigorous analysis is required to provide an explanation to the apparent disparity, here we can postulate that investors perceive R&D intensive firms' stock as a safer asset. More generally, however, the disparity implies that the relationship between the strength of shock transmission and R&D depends on the time horizon, with a stronger transmission through R&D intensive firms in the long-run but a weaker transmission through these firms in the short-run.

We conduct several other tests to check for robustness. As a first test, we use a two-stage approach instead of the single stage regression above. In the first stage, we use daily data to measure the sensitivity of a firms' stock prices to term premium shocks by estimating the equation below separately for each firm and quarter in our sample:

$$r_{i,q,t} = \alpha^r_{i,q} + \beta^r_{i,q} tp_{q,t} + \eta^r_{i,q} r^{3m}_{q,t} + \mu^r_{i,q} \left[E(h_{q,t}) - r^{3m}_{q,t}\right] + \varepsilon^r_{i,q,t} \tag{33}$$

where i, q and t index firms, the quarter and the day within the quarter, respectively. Unlike the exercise above, we do not focus on FOMC announcement days since doing so for each firm and quarter separately does not provide sufficient observations for statistical power. We do, however, restrict our sample by to days when extreme term premium shock values are observed. Extreme term premium shock values are defined as the observations for $tp_{q,t}$ that are at least one standard deviation away from the mean. This approach helps us eliminate noise in the data and allows us to more clearly capture the effects of term premium shocks on stock prices. After choosing the extreme days, the sample has more than two million observations. At this stage, we narrow the sample by focusing on firms with more than the median number of observations at the quarterly level, which ensures that each firm has at least 22 observations in a given quarter. After this first stage regression, we obtain one estimate of the term premium shock coefficient for each firm and quarter.

While we do not report the estimated coefficients for each firm and quarter, it is important to note that they are mostly negative, consistent with the results above, with an average value of -3.45. In the second stage, we use the estimated term premium sensitivities, $\hat{\beta}_i^r$, as the dependent variable in the following panel model:

$$\hat{\beta}_{i,q}^r = \alpha_i^{r_2} + \gamma_i^{r_2} rd_{i,q} + \Lambda_i C_{i,q} + \varepsilon_{i,q} \tag{34}$$

where $rd_{i,q}$ and $C_{i,q}$ are the R&D-to-total-assets ratio and a vector of the financial ratios for firm i in quarter q. The results from the estimation of equation (34) are displayed in the second column of Table 6. Here the focus is on the coefficient of the R&D variable. The positive value of this coefficient, given that the negative sensitivities in the first stage, implies that R&D activity has a mitigating impact on stock returns' responsiveness to term premium shocks. This is consistent with the results from our single stage estimation.

Similar to our baseline tests, we also consider the specification without R&D expenditures, equation (33). The results reported in columns 2 and 3 of Table 6 reveal a similar inference.

Firms that do not report R&D activity are more sensitive to the term premium shock, compared to firms with R&D.[14] We should also mention that when we use term premium shocks instead of monetary shocks in our estimations with quarterly sales data, we similarly find negative and significant coefficients for the interaction term with R&D intensity, further suggesting that R&D's effect on monetary policy sensitivity depends on the time horizon.[15]

Throughout our estimations, we also find that it is the term premium shock and not the expected term premium that is negatively related to stock returns. This implies that while an unexpected increase in the premium for long-term risk can shift demand from stocks to bonds and thus lower stock returns, an expected positive change in the premium can increase the returns on bonds and stocks simultaneously as investors who require higher returns from both assets. Also, the positive relationship could arise if the higher expected premium is driven by expectations of higher inflation as stocks serve as inflation hedges. The significant coefficients of the other firm specific variables indicate that more profitable, liquid and financially leveraged firms have higher stock returns.

5 Concluding remarks

In this paper we demonstrated that innovation activity, particularly R&D, forms an important channel through which demand and financial shocks are transmitted to the economy. We constructed and estimated a New Keynesian DSGE model with an endogeneous growth mechanism that depends on R&D. Focusing on monetary transmission and comparing the estimation results from the model with and without innovation activity, we found that monetary policy shocks' contribution to output volatility is much higher in the model with innovation activity. An extension of the model with two types of intermediate good producers, ones that innovate and ones that adopt technologies, revealed similar inferences: Monetary shocks are transmitted through the production of innovators rather than adopters' output.

[14]The difference in the term premium shocks' coefficient values, reported in columns 2 and 3, is significant at the 1 percent level.

[15]The coefficients of the term premium shock variable were, however, insignificant in these estimations.

In the second half of the paper, we used quarterly firm-level data and uncovered a positive relationship between firms' R&D intensity and the sensitivity of their sales to monetary policy that supports our DSGE model results and that is quantitatively large. Further analysis with quarterly data revealed a stronger relationship between monetary transmission and R&D for larger monetary policy shocks, and that the impact of firms' R&D activity on monetary policy sensitivity is independent of firms' size. Using daily data to approximate the relationship between R&D intensity and the more immediate impact of financial shocks, we observed, in contrast to the inferences from our quarterly analysis, that R&D intensity mitigates the effect of term premium shocks on stock returns. The overall inference was that while R&D activity can amplify shock transmission at the quarterly frequency, it can play an insulating role at higher frequencies.

The results in this paper inform the fundamental debate between real business cycle theory and Keynesian economics by attributing a greater role to supply side factors in determining business cycles. We do also however detect that it is the structure of the supply side and not necessarily the shocks that originate within it that are crucial. It would be insightful for future research to conduct a horse-race between models with nominal frictions and our model with the endogenous growth mechanism. Specifically, it would be interesting to omit financial frictions in the model with R&D activity and determine how much the contribution of demand/financial shocks to output volatility is reduced compare to doing so in a model without R&D activity.

There are two simplifications that we made in our model for tractability. First, the rate of innovation spillover across firms, in both models that we considered, is a parameter. Second, the model has no link between R&D activity and price mark-ups. It would be difficult but beneficial for future research to incorporate endogenous mechanisms with strategic decision-making that determines the rate of spillover and the profitability of R&D activity.

Finally, we used observations for the large public firms that are included in COMPUSTAT database. While a majority of the R&D activity is conducted by large firms, it would be interesting for future studies to consider a broader group of firms to determine the impact of R&D intensity on monetary policy sensitivity. A natural way to proceed would be to investigate the production activity of the firms included in National Science Foundation's BRDIS and SIRD databases to determine whether the positive relationship between R&D intensity and monetary policy sensitivity that we uncovered also holds for smaller firms.

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Appendix A. Rest of the model

This appendix describes the remaining agents and their optimization problems.

A.1. Households

The economy includes a continuum of households who are, indexed by i, have infinite lives and decide how much to work, $l_t(i)$, save and consume, $c_t(i)$, in each period. Household i makes these decisions to maximize the following life-time utility function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\log\left[c_t(i) - \zeta c_{t-1}\right] - \tau \frac{l_t(i)^{1+\vartheta}}{1+\vartheta} \right), \tag{A.1}$$

where β and ϑ are the growth-adjusted discount factor and the inverse elasticity of labor supply, respectively. Consumers exhibit external habit formation that is regulated by the parameter ζ. The parameter τ is included and calibrated so that labor supply is equal to one at steady state. Household i faces the following constraint when maximizing the utility function:

$$\begin{aligned} & c_t(i) + q_t\left[k_t(i) - (1-\delta) k_{t-1}(i)\right] + \frac{b_t(i)}{r_t p_t} \\ & \leq \frac{w_t(i)}{p_t} l_t(i) + \frac{r_{k,t}}{\varepsilon_{k,t-1}} k_{t-1}(i) + \frac{b_{t-1}(i)}{p_t} + \frac{\Pi_{i,t}}{p_t} - \frac{T_t}{p_t} \\ & - \frac{\kappa_w}{2} \left(\frac{w_t(i)/w_{t-1}(i)}{\gamma \pi_{t-1}^{\varsigma_w} \pi^{1-\varsigma_w}} - 1 \right)^2 \frac{w_t}{p_t} l_t \end{aligned} \tag{A.2}$$

w_t and p_t denote aggregate wages and prices in the economy and $w_t(i)$ represents household i's wages. Households are the owners of capital. Household i sells its undepreciated capital to capital producers and purchases $k_t(i)$ units of capital from these producers at the price of q_t per unit and rent these to intermediate goods producers from whom they receive the rental rate of $r_{k,t}$. Households can also by holding one-period nominal bonds, $b_t(i)$, with r_t representing the interest on these bonds. The households pay lump-sum taxes, T_t, to the government and collect profits, $\Pi_t(i)$ from the intermediate good producers that is evenly distributed across households. $\varepsilon_{k,t}$ in the budget constraint above is an exogenous change in the relative cost of capital (or credit spreads) that is commonly interpreted as a change in the liquidity demand (e.g., Anzoategui et al., 2019) or a change in the volatility of an idiosyncratic capital return shocks that capital owners face (Bernanke et al. 1999). As in Rotemberg (1982) wage stickiness is introduced in our model via quadratic wage adjustment costs. Here κ_w and ς_w govern the probability of keeping wages constant and the degree of indexation, respectively.[16] γ in the above equation is the economic growth rate and the inflation rate is given by $\pi_t = p_t/p_{t-1}$.

Perfectly competitive labor aggregators collect households' labor services and transform them into an aggregate labor unit, l_t, as follows:

$$l_t = \left[\int_0^n [l_t(i)]^{\frac{\eta_{l,t}-1}{\eta_{l,t}}} di\right]^{\frac{\eta_{l,t}}{\eta_t-1}} \tag{A.3}$$

where $\eta_{l,t}$ is the elasticity of substitution between labor services that is related to wage mark-up, $\theta_{w,t}$, as follows: $\theta_{w,t} = \frac{\eta_{l,t}}{\eta_{l,t}-1}$.The aggregate labor services are then hired by intermediate good producers. The maximization problem of labor aggregators produces the following labor demand condition:

$$l_t(i) = \left(\frac{w_t(i)}{w_t}\right)^{-\eta_t} \tag{A.4}$$

Here we assume that the time-varying wage mark-up follows an AR(1) process given by,

$$\log\theta_{w,t} = (1-\rho_w)\,\eta/(\eta-1) + \rho_w \log\theta_{w,t-1} + \varepsilon_{w,t} \tag{A.5}$$

where θ_w captures the mark-up over the marginal rate of substitution between leisure and consumption, ρ_w is the persistence parameter and $\varepsilon_{w,t}$ represents a wage mark-up shock.

The consumers utility maximization problem with respect to bond and capital holdings produce the following two conditions:

$$1 = E_t\left[\left(\beta\frac{\lambda_{t+1}(i)}{\lambda_t(i)}\right)\frac{r_t}{\pi_{t+1}}\right], \tag{A.6}$$

[16]As in Smets and Wouters (2007) $\kappa_w = (1-\xi_w)\left(1-\xi_w\widetilde{\beta}\right)/6\xi_w$,where ξ_w is the probability of keeping wages the same.

$$1 = E_t\left[\left(\beta\frac{\lambda_{t+1}(i)}{\lambda_t(i)}\right)\frac{(1-\delta)\,q_{t+1}+rk_{t+1}-\varepsilon_{k,t}}{q_t}\right] \tag{A.7}$$

where $\lambda_t(i) = [p_t(c_t(i)-\zeta c_{t-1})]^{-1}$ is the Lagrangian multiplier on the household i's budget constraint. The conditions in linearized form are given by,

$$\widehat{c}_t = \frac{\zeta/\gamma}{1+\zeta/\gamma}(\widehat{c}_{t-1}-\widehat{\gamma}_t)+\frac{1}{1+\zeta/\gamma}E_t\left[\widehat{c}_{t+1}+\widehat{\gamma}_{t+1}\right]-\frac{1-\zeta/\gamma}{1+\zeta/\gamma}(\widehat{r}_t-E_t\widehat{\pi}_{t+1}) \tag{A.8}$$

$$\widehat{q}_t = \frac{(1-\delta)\,\beta}{\gamma}E_t\left[\widehat{q}_{t+1}\right]+\left(1-\frac{(1-\delta)\,\beta}{\gamma}\right)E_t\left[\widehat{r}_{k,t+1}\right]-(\widehat{r}_t-E_t\widehat{\pi}_{t+1}) \tag{A.9}$$

Labor supply decisions and wage setting behavior yield the two conditions below.

$$l_t(i)^{\vartheta} = \lambda_t\Omega_{H,t}w_t(i), \tag{A.10}$$

$$\begin{aligned}
&\kappa_w\left(\frac{\pi_t^w(i)}{\pi_{t-1}^{\varsigma_w}\pi^{1-\varsigma_w}}-1\right)\frac{\pi_t^w(i)}{\pi_{t-1}^{\varsigma_w}\pi^{1-\varsigma_w}}-\frac{l_t(i)}{l_t}\left(1+(1-\Omega_{H,t})\,\eta_{l,t}\right) \\
&= E_t\left\{\kappa_w\beta\frac{\lambda_{t+1}}{\lambda_t}\left(\frac{\pi_{t+1}^w(i)}{\pi_t^{\varsigma_w}\pi^{1-\varsigma_w}}-1\right)\frac{\left(\pi_{t+1}^w(i)\right)^2}{\pi_t^{\varsigma_w}\pi^{1-\varsigma_w}}\frac{l_{t+1}}{l_t}\right\}-\left(\eta_{l,t}-1\right)(1-\Omega_{H,t}\theta_{w,t}).
\end{aligned} \tag{A.11}$$

where $\Omega_{H,t} = w_t(i)\left(\frac{l_t(i)}{l_t}\right)^{1/\left(\eta_{l,t}-1\right)}$ is household i's Lagrangian multiplier on the budget constraint of labor intermediaries and wage inflation is given by $\pi_t^w(i) = w_t(i)/w_{t-1}(i)$. These two conditions are combined and linearized to produce the following New-Keynesian wage Phillips equation:

$$\begin{aligned}
&\widehat{\pi}_t^w-\varsigma_w\widehat{\pi}_{t-1} = \beta\left(E_t\widehat{\pi}_{t+1}^w-\varsigma_w\widehat{\pi}_t\right) \\
&+\frac{\eta_l-1}{\kappa_w}\left(\vartheta\widehat{l}_t+\frac{1}{1-\zeta/\gamma}\widehat{c}_t-\frac{\zeta/\gamma}{1-\zeta/\gamma}(\widehat{c}_{t-1}-\widehat{\gamma}_t)-\widehat{w}_t+\theta_{w,t}\right)
\end{aligned} \tag{A.12}$$

A.2. Capital producers

Perfectly competitive capital producers convert the final goods they purchase from final goods producers, at the price of P_t, and the undepreciated capital they purchase from households, at the price of Q_t, into new capital. They then sell the newly produced capital to households at a price of

Q_t. Capital producers' life-time profit maximization problem is given by,

$$\max\ E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[q_{t-1}k_t - q_{t-1}(1-\delta)k_{t-1} - i_t\right] \tag{A.13}$$
$$s.t. \qquad k_t = (1-\delta)k_{t-1} + \left[1 - \frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2\right]\varepsilon_{i,t}i_t.$$

where δ represents the depreciation rate. The capital producers face quadratic costs to adjusting investment, with κ_i regulating the level of these costs and their future profits are discounted by the households' stochastic discount factor. We assume that $\varepsilon_{i,t}$ is an investment shock that follows an AR(1) process. This variable represents a structural change in investment-specific technologies. Maximization with respect to investment produces the following condition:

$$q_{t-1}\varepsilon_{i,t}\left[1 - \frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2 - \kappa_i\left(\frac{i_t}{i_{t-1}} - 1\right)\frac{i_t}{i_{t-1}}\right] + E_t\left[\left(\beta\frac{\lambda_{t+1}}{\lambda_t}\right)\kappa_i q_t \varepsilon_{i,t+1}\left(\frac{i_{t+1}}{i_t} - 1\right)\frac{i_{t+1}^2}{i_t^2}\right] - 1 = 0 \tag{A.14}$$

and log-linearization yields the following investment Euler equation:

$$\widehat{i}_t = \frac{1}{1+\beta}\widehat{i}_{t-1} + \frac{\beta}{1+\beta}E_t\widehat{i}_{t+1} + \frac{1}{(1+\beta)\kappa_i}\left(\widehat{q}_t + \widehat{\varepsilon}_{i,t}\right) \tag{A.15}$$

A.3. Government spending and market clearing

The government collects lump-sum taxes, T_t and issues discount bonds to finance its real expenditures, g_t, and its debt payments so that,

$$g_t + \frac{b_{t-1}}{p_t} = T_t + \frac{b_t}{p_t r_t} \tag{A.16}$$

g_t follows an AR(1) process given by,

$$\log\left(\frac{g_t}{A_t}\right) = (1-\rho_g)\log g + \rho_g \log\left(\frac{g_{t-1}}{A_{t-1}}\right) + \varepsilon_{g,t} \tag{A.17}$$

where $\varepsilon_{g,t}$ is a government spending shock. This condition can be represented in the following log-linearized form:

$$\widehat{g}_t = \rho_g \widehat{g}_{t-1} + \varepsilon_{g,t} \tag{A.18}$$

The resource constraint for the whole economy is as follows:

$$y_t = c_t + i_t + g_t + \frac{\kappa_p}{2}\left(\frac{\pi_t}{\pi_{t-1}^{\varsigma_p}\pi^{1-\varsigma_p}} - 1\right)^2 y_t \tag{A.19}$$

This condition in log-linearized form is given by,

$$\frac{c}{y}\widehat{c}_t + \frac{i}{y}\widehat{i}_t + \frac{g}{y}\widehat{g}_t = \widehat{y}_t \tag{A.20}$$

Appendix B. Steady state, prior distributions and posterior estimates

This appendix lists the steady state conditions in our model that are used to pin down the level parameter values that cannot be estimated. We also report the prior and posterior distributions for the estimated parameters.

B.1. Steady state conditions

Along the balanced growth path, the growth factor is given by,

$$\gamma = e^{\nu l^r} \tag{B.1}$$

Optimality conditions

Capital:

$$\frac{\alpha}{\theta_p} = r_k \frac{k/\gamma}{y} \tag{B.2}$$

Production labor:

$$\frac{1-\alpha}{\theta_p} = \frac{w l^p}{y} \tag{B.3}$$

Capacity utilization:

$$\kappa_u = r_k \text{ and } u = 1 \tag{B.4}$$

R&D:

$$w = \mu \nu \tag{B.5}$$

Knowledge stock:

$$\mu = \frac{(1-\alpha) y \eta}{(1-\beta)\,\theta_p} \tag{B.6}$$

Prices:

$$1 = \Omega \theta_p \tag{B.7}$$

Production function:

$$y = \left(\frac{k}{\gamma}\right)^{\alpha} l^p \Longrightarrow y = \left(\frac{k/\gamma}{y}\right)^{\frac{\alpha}{1-\alpha}} \tag{B.8}$$

Feasibility condition:

$$\frac{c}{y}+\frac{i}{y}+\frac{g}{y}=1 \Longrightarrow \frac{c}{y}=1-\frac{i}{y}-\frac{g}{y} \tag{B.9}$$

To pind down l^r *we* use the economic growth rate, γ, and the income share of R&D services, $\frac{wl^r}{y}$, as data targets. We then use the following conditions:

$$\gamma=e^{\nu l^r} \Longrightarrow \nu=\frac{\log\gamma}{l^r} \tag{B.10}$$

which implies

$$\frac{wl^r}{(wl^r+wl^p)(1-\alpha)}=\frac{wl^r}{y}=\frac{(1-\alpha)\,\nu}{(1-\beta)\,\theta_p}\eta l^r=\frac{(1-\alpha)\log\gamma}{(1-\beta)\,\theta_p}\eta. \tag{B.11}$$

$$\frac{c}{y}+\frac{i}{y}+\frac{g}{y}=1 \text{ and } \frac{i}{y}=1-\frac{1-\delta}{\gamma} \text{ and } \frac{wl^p}{y}=\frac{1-\alpha}{\theta_p} \tag{B.12}$$

As discussed in the paper we set steady-state values as $\gamma=1.005$, $\frac{wl^r}{y}=0.1$, and $l^r=0.03$ which requires the following calibration:

$$\frac{wl^r}{y}=\frac{(1-\alpha)\log\gamma}{(1-\beta)\,\theta_p}\eta \Longrightarrow \eta=\frac{\frac{wl^r}{y}(1-\beta)\,\theta_p}{(1-\alpha)\log\gamma}. \tag{B.13}$$

$$\nu=\frac{\log\gamma}{l^r} \tag{B.14}$$

Following standard practice we also set the time discount parameter, β, the share of labor income, α, the quarterly depreciation rate, δ, and the share of government spending, g/y, to 0.995, 0.3, 0.025, 0.2, respectively. Finally, the labor parameter in the utility function, $\tau=\frac{(1-\alpha)}{\xi_w(1-\zeta)c/y}$ so that labor supply is equal to 1 at steady state.

B.1. Prior distributions and posterior estimates

The prior distributions for estimated parameters, reported in Table B.1, closely follow those in Smets and Wouters (2007) and Gilchrist et al. (2009). The price rigidity parameters ξ_p and ξ_w have beta priors with mean 0.5 (implying an average of 2 quarter price and wage stickiness) and standard deviation 0.1. The steady state price and wage mark up parameters, η_y and η_l have a gamma prior with mean and standard deviation of 5 and 1.5, respectively.

The habit persistence parameter, ζ, has a beta distribution with a mean and standard deviation of 0.7 and 0.1, respectively. The Frisch-elasticity parameter ϑ has a normal prior with a mean and standard deviation of 2 and 0.75, respectively. The mean value of 0.5 for the capacity utilization elasticity parameter, ϖ, implies unit elasticity of utilization. We assume that this parameter has beta a prior distribution with a standard deviation of 0.2. The parameter regulating investment adjustment costs, κ_i, has a normal prior with mean and standard deviation of 4 and 1.5, respectively. We follow the use the prior distribution for the R&D adjustment cost parameter, κ_r.

For the Taylor rule parameters, we assume that the response coefficients on output and inflation, α_y and α_π, have normal distributions with mean 0.25 and standard deviation 0.12, and a mean of 1.5 and standard deviation 0.25, respectively. Finally, the interest rate smoothing parameter, ρ, has a normal distribution with mean and standard deviation of 0.75 and 0.1, respectively.

I assume that all shock persistence parameters have beta priors with mean 0.5 and standard deviation 0.2, and that the priors for their standard deviations are inverse gamma distributions with mean 0.005 and infinite variance. These are fairly uninformative priors.

The posterior estimates are displayed in column 3 in Tables B.1. For a majority of the parameters we observe that the posterior mean values are considerably different from their corresponding prior mean values suggesting that the dataset is informative.

Table B.1. Posterior distributions and posterior estimates

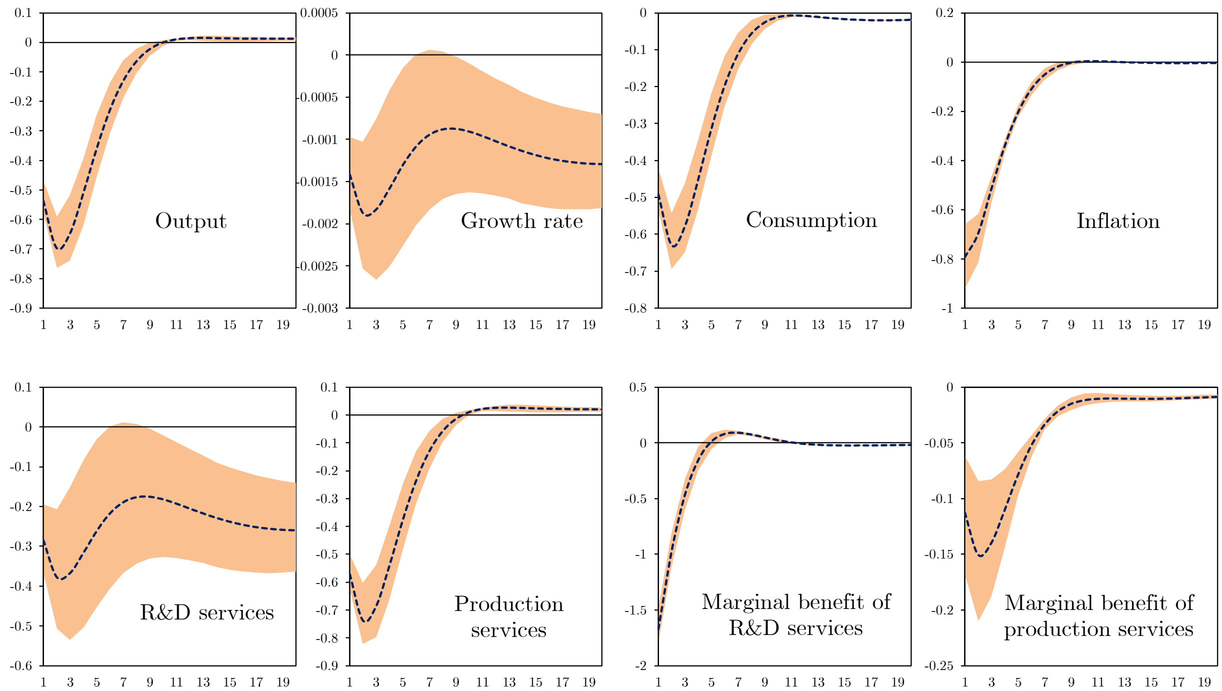
	Prior Densities	Posterior Means
ζ	B (0.7, 0.1)	0.709
ϑ	N (2, 0.75)	3.594
ϖ	B (0.5, 0.2)	0.488
κ_i	N (4, 1.5)	4.798
κ_r	N (4, 1.5)	8.096
ξ_p	B (0.5, 0.1)	0.049
ξ_w	B (0.5, 0.1)	0.084
η_y	G (5, 1.5)	4.309
η_l	G (5, 1.5)	1.114
ρ	N (0.75, 0.1)	0.937
α_π	N (1.5, 0.25)	1.670
α_y	N (0.25, 0.12)	0.448
Shock persistence parameters		
government expenditure	B (0.5, 0.2)	0.934
monetary policy	B (0.5, 0.2)	0.694
price mark-up	B (0.5, 0.2)	0.575
wage mark-up	B (0.5, 0.2)	0.359
cost of capital	B (0.5, 0.2)	0.484
investment	B (0.5, 0.2)	0.262
total factor productivity	B (0.5, 0.2)	0.698
standing on shoulders	B (0.5, 0.2)	0.403
Shock standard deviations		
government expenditure	IG (0.5%, inf)	0.008
monetary policy	IG (0.5%, inf)	0.001
price mark-up	IG (0.5%, inf)	0.016
wage mark-up	IG (0.5%, inf)	0.039
cost of capital	IG (0.5%, inf)	0.028
investment	IG (0.5%, inf)	0.200
total factor productivity	IG (0.5%, inf)	0.009
standing on shoulders	IG (0.5%, inf)	0.074

Appendix C. Data description

Table C.1. Data definitions and sources

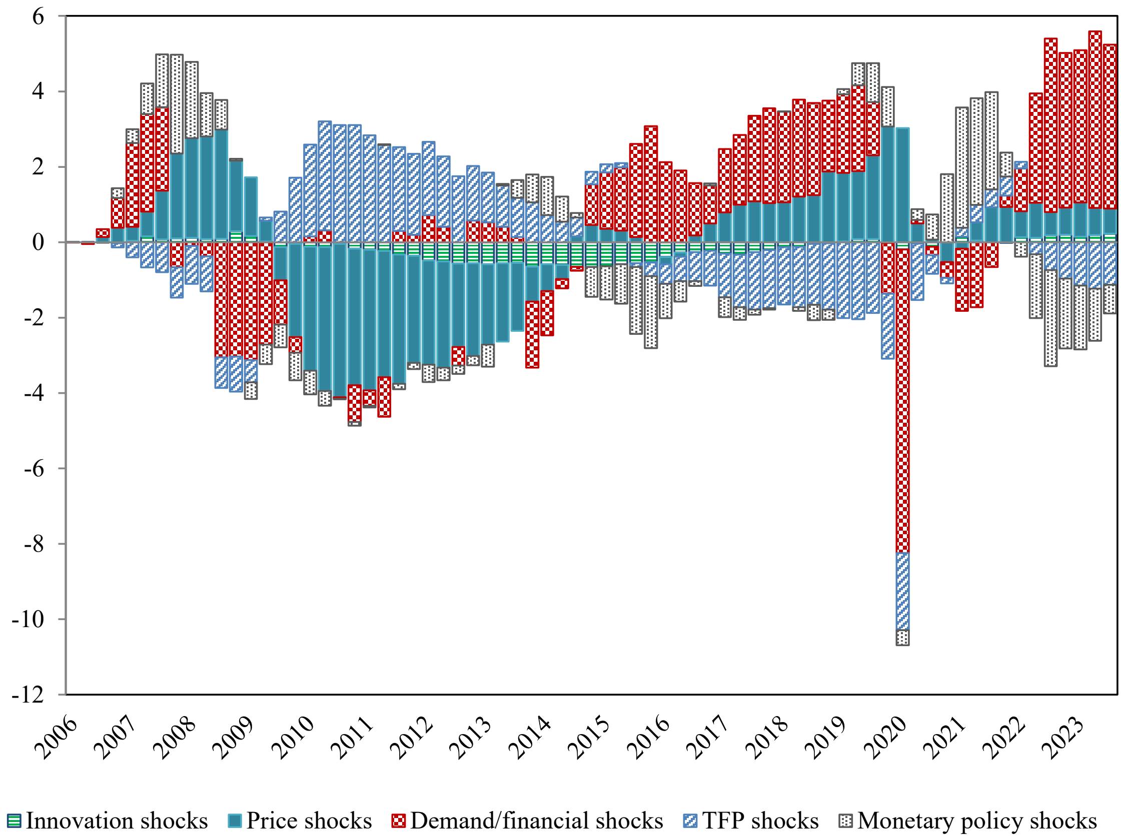
Variable	Description	Data Source
R&D-to-assets ratio	XRDQ/ATQ, the ratio of quarterly research and development expenses (XRDQ) to total assets (ATQ)	Compustat
Sales growth rate	Change in the natural logarithm of quarterly sales (SALEQ)	Compustat
Leverage	(DLCQ+DLTTQ)/ ATQ, the ratio of total quarterly long term debt (DLCQ+DLTTQ) to assets ATQ	Compustat
Tobin s Q	(CSHOQ*PRCCQ+ATQ-CEQQ)/ATQ, the ratio of quarterly market value of equity (CSHOQ*PRCCQ) and liabilities (ATQ-CEQQ) to assets (ATQ)	Compustat
Cash	(OIADPQ + DPQ +XRDQ)/ATQ, Quarterly operating income after depreciation (OIADPQ) and depreciation and amortization expense (DPQ) and research and development expense (XRDQ) as a share of assets (ATQ).	Compustat
Daily return of a stock	PRCCD, Closing price of a security for each trading day	CRSP/Compustat Merged Database
Monetary Policy Shocks	BRW Fed Monetary Policy Shock	Bu, Rogers, Wu (2019)
Federal Funds Rate	Federal funds effective rate	Federal Reserve Economic Data
Wu-Xia Rate	Wu-Xia Shadow Federal Funds Rate	Wu and Xia (2016, 2017, 2020)
GDP Deflator	Gross Domestic Product: Implicit Price Deflator, Index, Quarterly, Seasonally adjusted	Federal Reserve Economic Data
Term Premium	Term premium on a 10 year zero coupon bond, Percent, Not seasonally adjusted	Federal Reserve Economic Data
r^{3m}	Yield on 3-month US Treasury bill secondary market rate	Federal Reserve Economic Data
E(h)	Average expected future 3 month T-bill rates over the horizon of 10 years.	Gurkaynak, Sack and Wright (2007)

Figure 1. Responses to a monetary policy shock



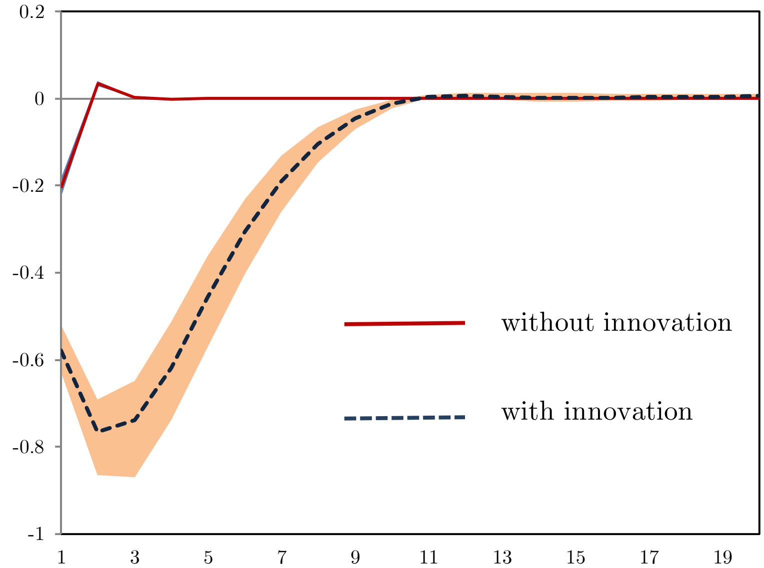
Notes: The figure shows the impulse responses to a one standard deviation shock to the shadow rate.

Figure 2. Historical decomposition of output, baseline estimation



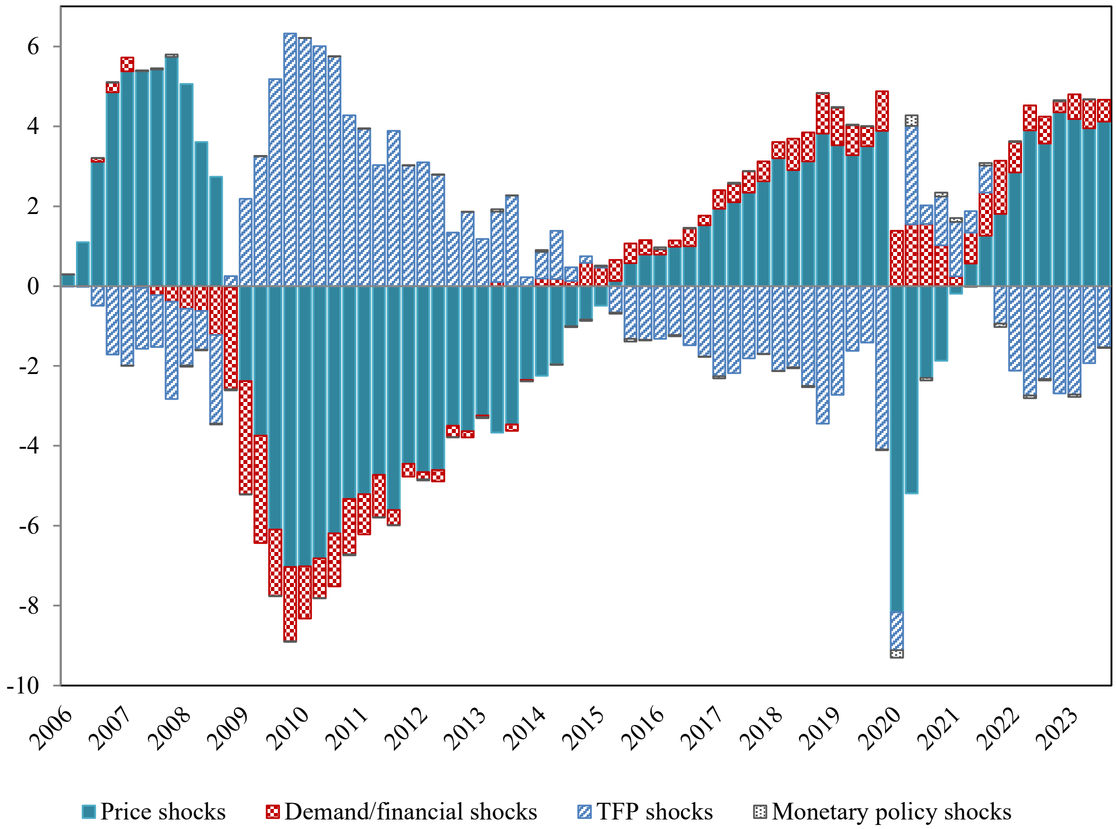
Note: The figures displays the contributions of shocks to the historical variance of real GDP in each quarter. The results for price shocks show the aggregate contribution of price and wage mark-up shocks. The results for demand/financial shocks show the aggregate contributions of investment, government spending and cost of capital shocks.

Figure 3. Output response to a monetary policy shock, baseline & w/o innovation



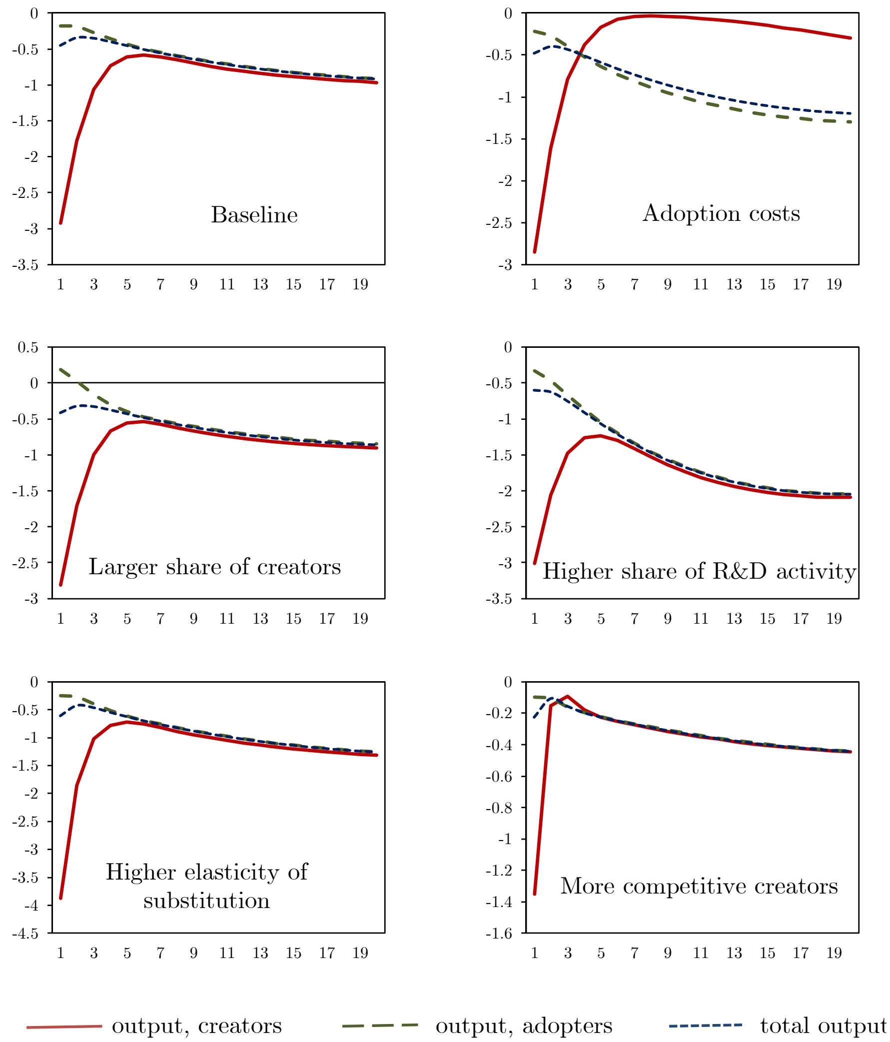
Notes: The figure shows the real GDP responses to a one standard deviation shock to the shadow rate. The responses labeled "without innovation" are obtained by estimating a model with exogenous growth that excludes the innovation process in our baseline model.

Figure 4. Historical decomposition of output, without innovation



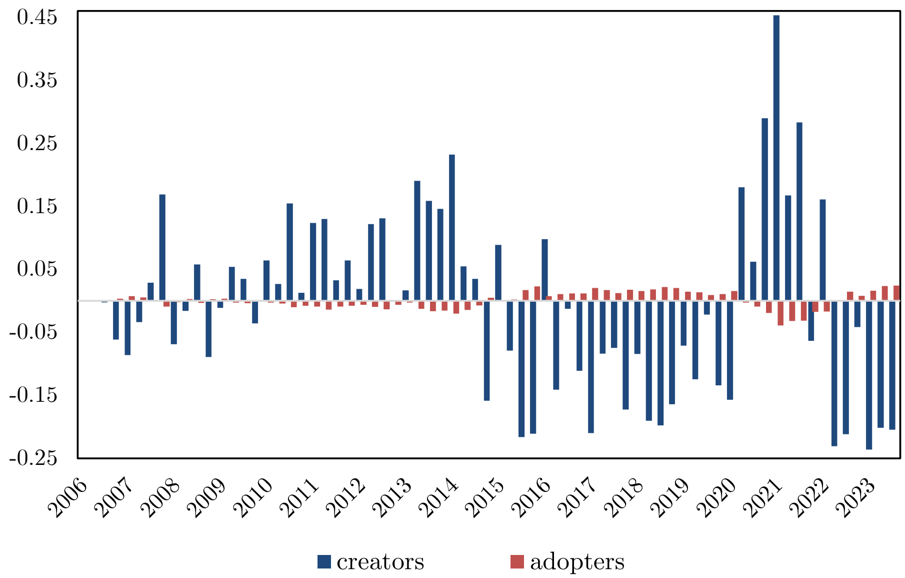
Note: The figures displays the contributions of shocks to the historical variance of real GDP that are obtained by estimating the model without the innovation process. The results for price shocks show the aggregate contribution of price and wage mark-up shocks. The results for demand/financial shocks show the aggregate contributions of investment, government spending and cost of capital shocks.

Figure 5. Creators versus adopters, output responses to a monetary policy shock



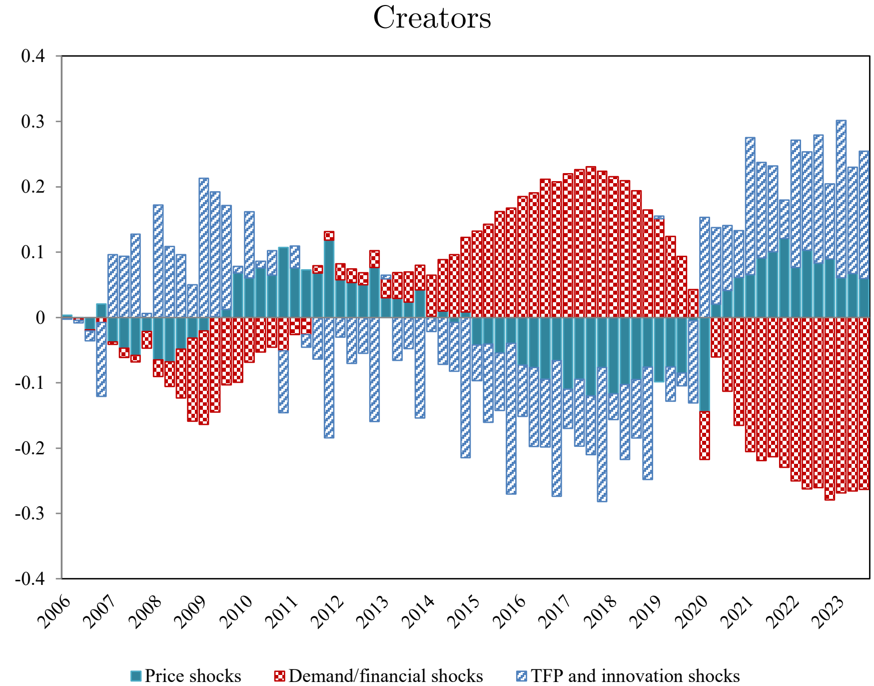
Notes: The figure shows the output responses to a one standard deviation shock to the shadow rate. Output responses are separately displayed for creators (firms with R&D activity), adopters (firms without R&D activity) and the whole industry.

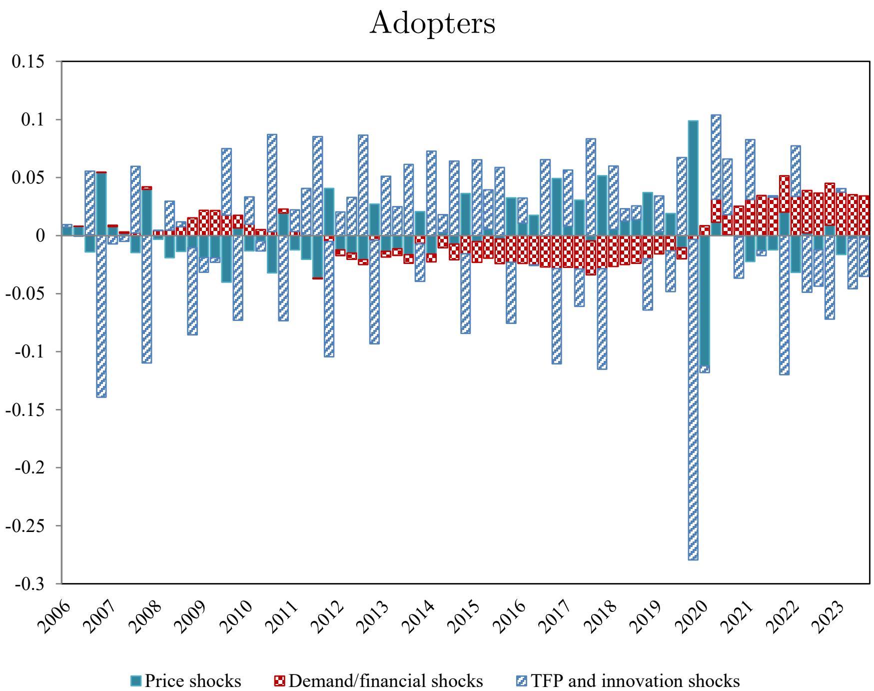
Figure 6. Contribution of monetary policy shocks to the historical decomposition of output



Note: The figures displays the contributions of monetary policy shocks to the historical variance of the real sale growth of firms that engage in R&D (creators) and firms that do not (adopters).

Figure 7. Contribution of shocks to output variation by type, creators versus adopters





Note: The figures displays the contributions of shocks to the historical variance of the real sale growth of firms that engage in R&D (creators) and firms that do not (adopters). The results for price shocks show the aggregate contribution of price and wage mark-up shocks. The results for demand/financial shocks show the aggregate contributions of investment, government spending and cost of capital shocks.

Table 1. Descriptive statistics

	Firms with R&D		Firms without R&D	
	Mean	Variance	Mean	Variance
Sales growth	0.6472	3.6994	0.3655	4.1257
R&D / Assets	2.2627	0.0546	-	-
Leverage	17.5875	4.0461	27.5441	6.5939
Liquidity	5.5732	1.3243	4.0445	0.0882
Tobin's Q	2.6699	3.9507	1.9547	1.645
Herfindahl-Hirschman index	0.32989		0.21329	
Number of unique firms in the sample	7,588		37,005	
Average number of firms per quarter	791		9,663	
Average size (Millions of Chained 2017 USD)	$6,631.336		$6,398.246	

Note: The description of the variables is provided in Appendix C, Table C.1.

Table 2. Baseline results

	Full sample	Firms with R&D, specification 1	Firms with R&D, specification 2	Firms without R&D
MPS	-0.0895	-0.119	-0.1429	-0.0356
	(0.003)***	(0.001)***	(0.000)***	(0.528)
R&D / Assets	2.4377	2.421		
	(0.000)***	(0.000)***		
Leverage	0.1757	0.2074	0.2417	0.0219
	(0.000)***	(0.000)***	(0.000)***	(0.491)
Cash flow / Assets	-2.1428	-2.1512	-1.5874	-1.4143
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Tobin's Q	0.0158	0.018	0.0196	0.024
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
MPS * R&D/Assets	-0.2033	-0.3406		
	(0.008)***	(0.039)**		
MPS * Leverage	0.0031	0.0202	0.051	-0.0456
	(0.445)	(0.842)	(0.920)	(0.008)***
MPS * Cash Flow / Assets	0.9875	1.0815	1.1058	-0.096
	(0.018)**	(0.019)**	(0.001)***	(0.032)**
MPS * Tobin's Q	-0.0044	-0.0059	-0.0042	0.0191
	(0.547)	(0.564)	(0.549)	(0.604)
Dependent variable (lags)	-1.6829	-1.6183	-1.6884	-2.6406
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Number of observations	49,251	36,657	36,575	12,448
AR 2 test	0.8599	0.7099	0.555	0.2918

Note: This table displays the results obtained by estimating equation (30). *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses are the p-values obtained from tests of joint significance.

Table 3. Large monetary policy shocks

	Full sample	Firms with R&D, specification 1	Firms with R&D, specification 2	Firms without R&D
MPS	-0.1989	-0.2384	-0.2169	-0.0155
	(0.000)***	(0.000)***	(0.000)***	(0.660)
R&D / Assets	1.8892	3.2229		
	(0.211)	(0.114)		
Leverage	0.1306	0.0929	0.0923	0.0957
	(0.246)	(0.503)	(0.508)	(0.539)
Cash flow / Assets	-1.773	-3.1269	-2.2906	-0.2827
	(0.150)	(0.047)**	(0.089)*	(0.709)
Tobin's Q	0.0183	0.0276	0.0278	-0.0469
	(0.462)	(0.325)	(0.318)	(0.108)
MPS * R&D/Assets	-2.6117	-1.8112		
	(0.090)*	(0.024)**		
MPS * Leverage	-0.0623	-0.115	-0.1134	-0.0012
	(0.338)	(0.012)**	(0.015)**	(0.321)
MPS * Cash Flow / Assets	1.3596	1.1051	2.519	1.119
	(0.563)	(0.290)	(0.081)*	(0.749)
MPS * Tobin's Q	-0.0235	-0.0041	-0.0016	0.0071
	(0.233)	(0.123)	(0.102)	(0.443)
Dependent variable lags	-3.2237	-2.8787	-2.8012	-0.1802
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Number of observations	6,084	4,491	4,491	1,584
AR 2 test	0.9323	0.7253	0.7494	0.4492

Note: This table displays the results obtained by estimating equation (30). Large monetary policy shocks are those that are 1/3 standard deviations away from the mean value. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses are the p-values obtained from tests of joint significance.

Table 4. Evidence from subsamples

	R&D sample	High RD	High R&D, High Assets	High R&D, Low Assets	Low R&D, High Assets	Low R&D, Low Assets
MPS	-0.0715	-0.0894	-0.0821	-0.0924	-0.0479	-0.0709
	(0.000)***	(0.000)***	(0.055)*	(0.021)**	(0.000)***	(0.000)***
Leverage	0.2006	0.2398	0.0476	0.2728	0.1034	0.1308
	(0.000)***	(0.000)***	(0.490)	(0.000)***	(0.118)	(0.002)***
Cash flow / Assets	-1.6907	-1.6408	-1.8334	-0.8126	-2.6191	-1.9347
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Tobin's Q	0.0177	0.0201	0.0300	0.0194	0.0388	0.018
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Dependent variable lags	-1.7598	-1.8174	-1.4954	-2.5992	-1.7732	-2.1801
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Number of observations	49,167	34,848	2,314	8,019	10,890	9,870
AR 2 test	0.7333	0.8202	0.922	0.878	0.511	0.843

Note: This table displays the results obtained by estimating equation (30) without the R&D variable and its interaction with the monetary policy shock series. Low and high assets and R&D firms refer to those that are in the bottom and top 40$^{\text{th}}$ percentile in terms of total assets and the R&D/Total assets ratio, respectively. *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses are the p-values obtained from tests of joint significance.

Table 5. Propensity score matching

	Treatment Effect	z	p-value
High R&D (p60)	-0.0496	-2.60	0.009
High R&D (p70)	-0.0535	-3.13	0.002
Positive R&D	-0.0484	-3.28	0.001
Low R&D (p30)	0.0721	2.73	0.006
Low R&D (p40)	0.0542	1.69	0.092

Note: This table displays the results obtained from the two stage propensity score matching exercise in Section 4.1. The first stage estimates the sensitivity of firms' real sales growth by using equation (31). The second stage uses the estimated sensitivities as the outcome variable and the R&D/Assets ratio as the treatment variable in a propensity score matching exercise. p60, p70, p30, p40 refer to the firms at the 60^{th} ,70^{th} , 30^{th} and 40^{th} percentile of distribution of the R&D/Assets ratio.

Table 6. Evidence from high frequency data

	Equation (32)			Equation (34)
	Whole sample	Firms with R&D, specification w/o R&D	Firms w/o R&D, specification w/o R&D	Whole sample
R&D/Assets	-0.1752	-	-	0.9890
	(0.000)***			(0.056)*
R&D/Assets * TP	2.2757	-	-	
	(0.001)***			
TP	-0.9348	-0.8529	-0.9754	
	(0.000)***	(0.000)***	(0.005)***	
Expected term premium	0.9528	0.9486	0.9332	
	(0.000)***	(0.000)***	(0.004)***	
Short-term yields	0.7038	0.6979	0.6910	
	(0.000)***	(0.000)***	(0.023)**	
Leverage	0.1326	0.1189	0.1209	0.1898
	(0.051)*	(0.099)*	(0.351)	(0.003)***
Cash flow / Assets	0.0960	0.0387	0.1069	0.6827
	(0.033)**	(0.265)	(0.251)	(0.006)***
Tobin's Q	0.0644	0.0797	0.0324	2.6084
	(0.135)	(0.603)	(0.015)**	(0.102)
Number of observations	94,847	77,347	17,496	40,109
Adjusted R-squared	0.6068	0.6262	0.4822	0.0441

Note: This table displays the results obtained by estimating equations (32) and (34). *, **, *** significant at 10%, 5%, 1%, respectively. The numbers reported in parentheses are the p-values obtained from tests of joint significance.