Innovation During Challenging Times: Patent-Based Innovation Shocks and Business Cycle Dynamics*

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Abstract

Do the economic effects of innovation differ across recessions and expansions? While recessions may create opportunities for investment in relatively cheaper, productivity-enhancing activities, financial constraints often limit access to the necessary capital. We explore this relationship by studying the propagation of patent-based innovation shocks, measured by changes in stock market valuations of firms receiving patent grants. We show that aggregate innovation shocks have a more pronounced impact during recessions, driven by a significant rise in private investment. Firm-level analysis further reveals that firms increase both capital investment and R&D spending in response to these shocks, with the effect amplified during downturns. Financial constraints play a crucial role: firms facing high default risk, particularly those under debt constraints, show limited response to innovation shocks. In contrast, firms that rely on equity financing face less binding constraints, allowing them to increase investment, especially during recessions.

Keywords: Innovation shocks, Patent-based innovation index, Financial frictions, Firm heterogeneity, State dependency

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1 Introduction

The extensive endogenous growth literature has documented that sustained economic growth is based on continuous technological advances and innovation (Solow, 1957, Romer, 1990, Aghion and Howitt, 1992). Recent research led by Beaudry and Portier (2006) has emphasized the crucial role of news about these advances—key drivers of economic growth—in shaping business cycle dynamics. In this paper, we investigate how this news propagates through the economy and whether the transmission varies depending on the state of the economy. To gain deeper insights into the transmission channels, we extend our analysis beyond traditional aggregate data, incorporating firm-level data to assess how different firms respond to these shocks, particularly in relation to prevailing economic conditions.

Understanding the timing of innovative activities has long been of great interest to economists. Since the work of Schumpeter (1942), many have argued that recessions create a favorable environment for productivity-enhancing activities. This perspective is grounded in the idea that such activities are more cost-effective during economic downturns, as the opportunity cost of forgone output and sales tends to be lower. As a result, firms may be more receptive to favorable innovation shocks during recessions. However, these downturns also increase the likelihood that firms will face financial constraints, which can hinder their ability to secure the necessary investments to fully capitalize on innovation.

Our contribution to this longstanding debate is to investigate how the economy responds to innovation shocks triggered by good news about patent grants, and whether the timing of this news matters. We show that it does. Specifically, when faced with an aggregate patent-based innovation shock, the economy exhibits a stronger response during recessions compared to normal times, with private investment playing a central role. This stronger response is also evident in firm-level data, where we find that news about patent grants stimulate investment and innovative activities, in particular during recessionary periods.

We identify innovation shocks by analyzing stock market reactions to news regarding individual patent grants, as proposed by Cascaldi-Garcia and Vukotić (2022), building on the work by Kogan, Papanikolaou, Seru, and Stoffman (2017). When a patent is granted, it reveals information about the future potential of the associated technology process or product, leading to a subsequent reaction in the stock market. Most patented technologies require additional time and resources to become operational. As a result, the immediate market reaction after a patent grant reflects market valuation of the innovation's future technological and economic potential.

Technology shocks are widely recognized as key drivers of business cycle fluctuations, with much of the focus on their macroeconomic impact. By analyzing patents, we shift focus to the underlying source of these innovations. Building on our aggregate findings, we examine how patent-based innovation shocks propagate through the economy at a disaggregated level. We study firm responses using detailed balance-sheet and income-statement data from the Compustat database, which tracks all publicly traded U.S. companies. These publicly listed firms account for roughly 60 percent of total U.S. investment, and the dynamics of their capital expenditures closely mirror those of the aggregate investment series reported by the U.S. Bureau of Economic Analysis.

While the earlier literature has examined the spread of technological news and innovation shocks at the aggregate level, this paper contributes by exploiting firm-level heterogeneity to investigate the transmission channels of these shocks and how they are shaped by the state of the economy. Examining the average reaction of firms is crucial, as they are catalysts of innovation and growth.[1] We find that firm-level investment responds positively to these patent-based innovation shocks. That holds true across patenting and non-patenting firms, and across sectors with varying degree of innovation activity. Thus, our findings highlight that innovation shocks not only affect the firms directly involved but also generate spillover effects across the economy. This suggests that these shocks, though originating from discrete innovations at the firm level, play a significant role in shaping business cycles at the aggregate level.

Another contribution of the paper is to consider the role of financial frictions in the propagation of innovation shocks at the firm-level. We find that firms in stronger financial positions—characterized by high liquidity, low leverage, and a greater distance to default—exhibit more significant responses in capital investment to innovation shocks. This enhanced responsiveness likely stems from their better access to funding and resources to take advantage of new technological opportunities. Furthermore, we observe that the effects of innovation shocks on firm investment, R&D expenditures, and other related variables are particularly pronounced during economic recessions. These findings support the Schumpeterian perspective that engaging in innovative activities may be less costly for firms during downturns. Furthermore, we provide evidence that the amplified impact of innovation shocks on firms with robust financial conditions or low credit risk becomes even more significant in periods of economic decline, highlighting the critical role of financial health in shaping firm responses to aggregate innovation shocks.

Finally, we take an additional step by examining different types of financial constraints, specifically comparing firms constrained by equity issuance versus those constrained by debt, in line with the methodologies of Hoberg and Maksimovic (2014) and Linn and Weagley (2023). This distinction is crucial, since the firm's distance to default depends on both equity and debt, each potentially limiting the firms' ability to adapt to

[1] Our focus is on average firm-level response to an aggregate innovation shock, and not on firm specific innovation to own firm-level response. There is a rich empirical literature on the effects of aggregate news shocks and the market response to the arrival of news about future innovations, which capture the diffusion of ideas and general equilibrium effects.

these shocks in different ways. We find that equity-constrained firms exhibit the largest investment response to innovation shocks, with the effect being even more pronounced during recessions. Notably, these firms tend to be R&D-intensive, and the public disclosure of innovation news in patent releases helps their equity issuance prospects in the face of an opportunity to invest.

Related Literature. Our paper speaks to multiple strands of the literature on innovation and firm dynamics over the business cycle. First, our paper provides valuable insights that contribute to a better understanding of anticipated technological shocks, as studied by Beaudry and Portier (2006). Since their pioneering work, relating news shocks to observable measures of technological improvements has been challenging.[2] Our approach offers a novel perspective by relying on micro-level data on patent grants and subsequent firms' stock market reactions, as in Cascaldi-Garcia and Vukotić (2022), essentially capturing shocks to innovative technological capacity brought about by patenting activity of firms. This paper explores how these shocks disseminate through the economy by studying the firms' dynamic responses. We find that firms' responses significantly depend on the prevailing economic conditions, which could have important policy implications. Overall, to the best of our knowledge, our paper is the first to investigate the state-dependent effects of innovation shocks.

Second, a general idea behind our work is related to the literature that links business-cycle fluctuations and long-term growth through the endogenous relationship between total factor productivity (TFP) and knowledge accumulation stemming from research and development (R&D) spending (e.g., Barlevy, 2007, Comin and Gertler, 2006, Anzoategui, Comin, Gertler, and Martinez, 2019, Bianchi, Kung, and Morales, 2019, and León-Ledesma and Shibayama, 2023). In addition, it is also related to the literature that investigates how investment in R&D changes over the business cycle. For example, we find that firm-level R&D investment is counter-cyclical conditional on innovation shocks, which is in line with the result of Aghion, Askenazy, Berman, Cette, and Eymard (2012) who analyze the R&D investment for a panel of French firms that are not credit constrained.

Third, we contribute to a large and growing literature on the state-dependent effects of macroeconomic and policy shocks. Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018), among others, investigate the effects of fiscal policy shocks during good and bad times and find mixed evidence. Tenreyro and Thwaites (2016) investigate state-dependent responses of the U.S. economy to monetary policy shocks, indicating that the effects of monetary policy are less powerful in recessions.

Fourth, our work is also related to the literature that uses firm data to uncover various

[2]The literature on technological news shocks is extensive. See, among others, Jaimovich and Rebelo (2009), Barsky and Sims (2011), Schmitt-Grohe and Uribe (2012), Forni, Gambetti, and Sala (2014), Crouzet and Oh (2016), Miranda-Agrippino, Hoke, and Bluwstein (2020), Kurmann and Sims (2021), Cascaldi-Garcia and Galvão (2021), Görtz, Tsoukalas, and Zanetti (2022b), and Cascaldi-Garcia (2024).

transmission channels, such as financial frictions, of other economic shocks, particularly monetary policy shocks. For example, Ottonello and Winberry (2020), Cloyne, Ferreira, Froemel, and Surico (2023), and Jeenas (2019) all investigate the investment channel of monetary policy and the role that financial constraints play in the transmission of shocks. In related work, Döttling and Ratnovski (2023) find that different types of investment of firms with relatively more intangible assets respond less to monetary policy.

Our paper is organized as follows. Section 2 explains the identification behind patent-based innovation shocks. Sections 3 and 4 provide comprehensive analysis of linear and state-dependent effects of innovation shocks at the aggregate and the firm-level. Section 5 concludes.

2 Patent-Based Innovation Shock

We use the aggregate quarterly patent innovation index constructed by Cascaldi-Garcia and Vukotić (2022) to measure the market valuation of future technological potentials. Figure 1 illustrates the evolution of the index for the post-World War II period, spanning from 1947:Q1 to 2019:Q4, which corresponds to the sample of our aggregate analysis. The aggregate index represents the total value of all patents granted to the firms in our sample during a specific quarter, scaled by the aggregate output. This scaling is consistent with an innovation model described by Atkeson and Burstein (2019), where firms generate monopoly profits through innovation. These profits are linearly related to both aggregate output and TFP. As described in great detail in Cascaldi-Garcia and Vukotić (2022), shocks to this measure are akin to a technological news shock.

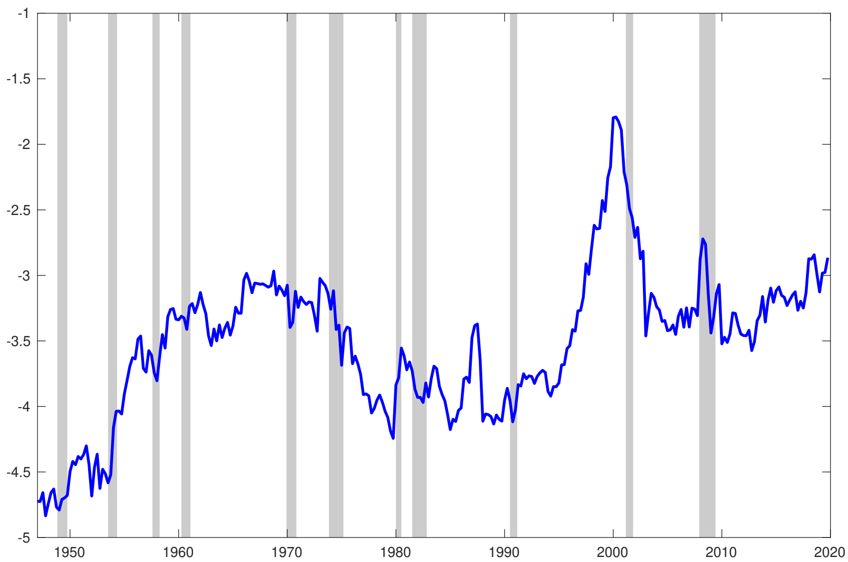
We obtain the economic value of each patent, based on the approach of Kogan et al. (2017), who extract this information using high-frequency movements in stock prices triggered by a patent grant. This approach effectively filters out noise and news unrelated to the patenting activity.[3]

The index effectively tracks periods of technological booms and slowdowns. For example, it increases during the substantial innovation surge in the 1960s and the early part of the 1970s, while its peak values align with the onset of the computing and telecommunications revolution during the 1990s and early 2000s. Subsequently, the index experienced a significant decline during the dot-com bubble but later stabilized.

We interpret exogenous variations in this index as aggregate *patent-based innovation shocks* because its movements are directly linked to patent grants and changes in firms' stock evaluations. These shocks relate closely to the original concept proposed by Beaudry and Portier (2006), which has spurred a significant literature on the impact of anticipated technological advancements on the economy. Our approach relies solely on micro-level

[3]The procedure for constructing a quarterly measure of the aggregate patent-based innovation index is explained in detail in Cascaldi-Garcia and Vukotić (2022).

Figure 1 Patent-Based Quarterly Innovation Index



Note: Log of the aggregate quarterly per capita patent-based innovation index constructed following the procedure described in Cascaldi-Garcia and Vukotić (2022), spanning from 1947:Q1 to 2019:Q4. The shaded areas represent the National Bureau of Economic Research (NBER) dated recessions.

patent data and corresponding stock market reactions, capturing the present value of expected revenues from innovation. However, our analysis differs from technological news shocks that encompass *all* anticipated information regarding future TFP movements, as our measure specifically focuses on patenting activity by publicly listed firms.

Given the extensive discussion on the benefits of this approach presented in Cascaldi-Garcia and Vukotić (2022)—such as avoiding the need of structural restrictions or the need of an empirical measure of TFP for identification—here we refrain from comparing our shocks with other approaches in the literature. Instead, we provide a brief justification for treating the shock we uncover as an innovation shock.

As stated by Griliches (1998), *"patent provides temporary monopoly for the inventor and forces the early disclosure of the information necessary for the production of this item or the operation of the new process."* Thus, each granted patent likely represents an innovation, conveying specific information about future potential of that innovation. One way to quantify this potential is by measuring stock market reactions to the information revealed at the time of the patent grant.[4] Most patented technologies require additional

[4]The response of market participants to this information, as highlighted by Kogan et al. (2017), complements our argument. Merely counting patents is insufficient for assessing future innovation potential, as the number alone obscures differences in the nature and expected outcomes of patents, which can vary in their effects on both firm-level and aggregate productivity. For instance, comparing the aggregate economic impact of a pharmaceutical patent to that of an electronics patent would be challenging.

time and resources to become operational, so the immediate market reaction to a patent grant reflects the market's valuation of its future technological and economic potential. Therefore, changes in these valuations capture shocks regarding the future potential of granted innovations, which is why we term these changes as patent-based innovation shocks.

2.1 Cyclicality of Innovation Measures

A key concern when examining the relationship between innovation and economic conditions is whether the act of innovating, specifically patenting, differs between recessions and stable economic periods. If innovation does indeed fluctuate with the business cycle, any asymmetric effects observed after innovations may be a result of these cyclical changes rather than the inherent characteristics of the innovations themselves.

To address this concern, we examine the cyclicality of several innovation indicators. It is important to note that while firms can choose when to apply for a patent, the timing of the patent grant is somewhat random. The median delay between patent application and issuance is approximately three years. This means that a firm might apply for a patent during normal times but receive the grant during a recession, or vice-versa. Alternatively, a firm could apply and be granted a patent during the same economic phase, which is more likely to occur in stable economic conditions due to the longer time frame for approval. We exploit this randomness in the patent issuance process, along with the information contained in the patent-based innovation index, to investigate how the economy responds to innovation shocks in different states of the economy.[5]

We also examine the relationship between common measures of innovative activity and real GDP at business cycle frequencies, using Hodrick-Prescott and bandpass filters with frequencies ranging from six to forty quarters, as outlined in Table 1. Our analysis indicates that R&D spending—often regarded as a key indicator of innovative activity—exhibits a significant correlation with real GDP at business cycle frequencies. Notably, this correlation nearly doubles at medium-cycle frequencies (forty to eighty quarters), although this is not shown here. In contrast, patenting activity, measured by the number of patent applications and patents granted, does not show any evidence of cyclicality. The correlation between these patent-related measures and real GDP is close to zero at business cycle frequencies, regardless of whether the Hodrick-Prescott or band-pass filter is applied.

[5] Notably, significant patents have been granted during recessions. For instance, patent number 6,292,834, was granted to Microsoft for dynamic bandwidth selection for efficient transmission of multimedia streams in a computer network during a recession on September 18, 2001. This patent had a substantial market valuation upon release and has also received numerous citations. It was filed during an expansion on March 14, 1997. Similarly, patent number 7,297,977, granted to Hewlett-Packard for a semiconductor device on November 20, 2007, is the third most cited patent in our database. It was filed during an expansion on March 12, 2004.

Table 1 Cross-correlations with real GDP for 1947:Q1-2019:Q4

	Business-cycle frequencies (HP)	Business-cycle frequencies (BP)
R&D Spending	0.42	0.32
Patent applications	-0.01	-0.01
Patent grants	-0.01	0.02
Lag between application and issuance	-0.01	0.01
Patent-based innovation index	0.15	0.12

Note: Business-cycle frequencies are extracted using the Hodrick and Prescott (HP) filter with a parameter value of $\lambda = 1600$ (column 1), as well as a band-pass filter with frequencies ranging from 6 to 40 quarters (column 2).

Based on the evidence discussed, we draw two key conclusions. First, the cyclicality of R&D spending suggests that using it as a proxy for innovation may mislead economic agents and econometricians into believing that fluctuations in business cycle movements of R&D are directly caused by innovation. In reality, these fluctuations may be influenced by other factors such as credit availability, financial constraints, risk aversion, uncertainty, and monetary or fiscal policies. Additionally, any analysis of the state-dependency of shocks to R&D spending may also confound potentially different economic effects in recessions and normal times with other cyclical factors that are state-dependent.

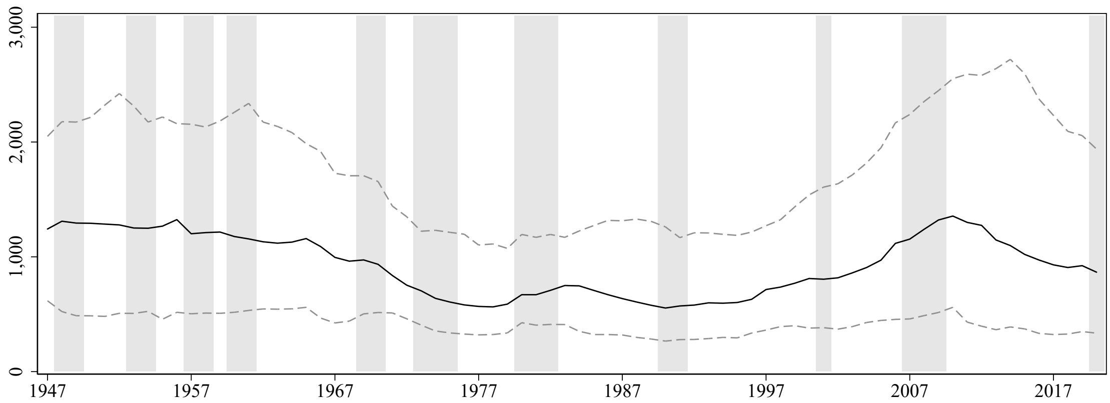
Second, the absence of cyclicality in patent applications and grants implies that while firms may choose to invest more in R&D during economic tranquil times, the actual outcome of innovation, as measured by patenting activity, is largely independent of the business cycle. This evidence reinforces the notion that true innovative ideas are rare (Bloom, Jones, Van Reenen, and Webb, 2020), as their emergence and subsequent patenting do not correlate with economic conditions. This distinction is crucial for differentiating cyclical factors unrelated to patenting from actual innovative activity. However, it is important to recognize that the quantity of patent applications or grants does not reflect the quality of innovations or their potential impact on future productivity.

Another potential concern is whether the lag between patent application and issuance exhibits cyclicality, even if the applications and grants themselves do not. As illustrated in Figure 2, the median delay (in days) from application to issuance has remained relatively stable, averaging 908 days since 1947. Furthermore, Table 1, shows no significant correlation between the lag time and GDP, effectively ruling out cyclicality.

Finally, we examine cyclicality of the patent-based innovation index. The index exhibits a low correlation with GDP. There are three possible explanations for this observed mild cyclicality.

First, because the patent-based index is scaled by aggregate GDP, the cyclicality and state-dependent effects may stem from the denominator. However, we will show that this is not the case. The state-dependent effects of innovation shocks remain consistent even

Figure 2 Median delays (in days) between patent applications and issuance



Note: The x-axis shows the year that the patent is issued. The solid line shows the median delay, in terms of days, between patent application and issuance. The dashed line show the 95 % confidence intervals.

when we scale the patent-based innovation index by total market capitalization instead of GDP (not shown).

Second, the positive correlation may suggest that GDP responds quickly to market-implied innovation, indicating that some economic effects of the innovation might be realized in the short term. This aligns with the concept of an expectation-driven technological shock within the business cycle, as described by Beaudry and Portier (2006). To address potential identification concerns, we include lagged GDP as a control variable in all our analyses to account for these cyclicality effects.

Lastly, the mild cyclicality could be influenced by the stock market valuations included in the index. Economic agents might respond differently to patent activity based on economic conditions, which could be driven by the innovation's inherent economic potential (fundamental factors) or by heightened optimism (non-fundamental factors). We test this hypothesis below.

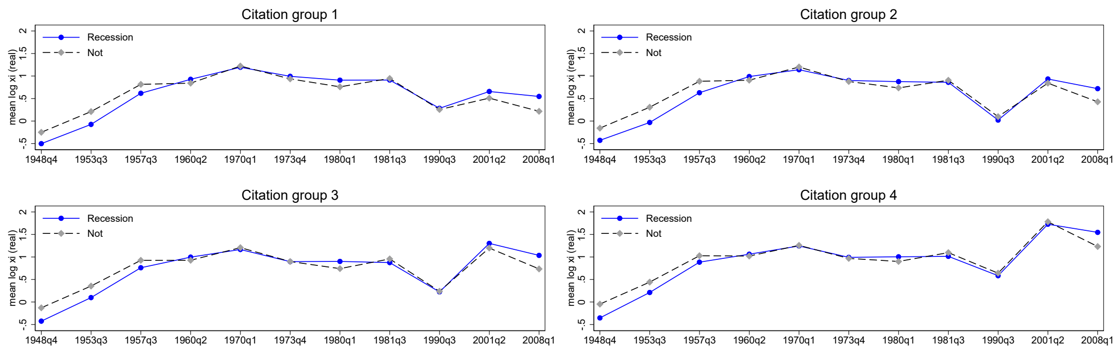
2.2 Stock Market Valuations During Recessions and Expansions

We assess whether the stock market reacts differently to similar innovations during recessions compared to normal times by analyzying the average stock market valuation of patents across the 11 different NBER-dated recessions in our sample. We also examine the corresponding normal time periods around these recessions.

To ensure a fair comparison of innovations with similar discovery scope, we categorize the patents based on their forward citations, which arguably reflect their scientific value. We divide these into quartiles for each relevant recession, taking into account that patents tend to accumulate more citations over time. Figure 3 shows the average real stock market valuations of patents released during each recession (blue dot), alongside the average valuations of similar patents in an 8-quarter window before and after each recession (gray dots). Each point on the x-axis corresponds to one of the 11 recessions in our sample.

Our analysis reveals no evidence that stock markets respond systematically more or less to innovations during recessions.[6] In fact, the recession valuations (blue dots) lie above the valuations of similar patents in normal times (gray dots) in the early part of the sample, but fall slightly below in periods like in 2000s. These results also hold when we consider the standard deviation of the stock market valuations as shown in Figure A.1 in the Appendix.

Figure 3 Average real market valuation across states of the economy



Note: Each panel of the figure shows the average real stock market valuation for a given recession (blue dots with solid lines) and the corresponding 8-quarter window before and after the recession (gray dots with dashed lines), for a given citation group. The citation groups are divided into four quartiles of citations for each recession.

Kogan et al. (2017) show that there is a strong and positive correlation between forward citations and patent market values. In a similar spirit to the exercise above, we also consider if this relationship differs for patents issued during recessions compared to those issued in normal times. We analyze the total number of future citations C received by patent j in relation to its estimated market value, ξ_j. We include a recession dummy variable, R_j, which equals 1 if the patent is issued in a recession and is 0 otherwise, as well as an interaction term between the recession dummy and the forward citations.[7]

$$\xi_j = a + b\,\text{Citations}_j + c\,R_j + d\,(R_j \times \text{Citations}_j) + f\,Z_j + u_j \tag{1}$$

To account for factors that may affect citations and patent valuations, we include a vector of control variables Z_j. This vector includes grant-year fixed effects, recognizing

[6] We get similar figures when we consider a window of 4 or 12 quarters.

[7] We consider the logarithm of ξ_j as the left-hand side variable, and the logarithm of $(1 + C_j)$ as the right-hand side variable for citations, closely following the specification in Kogan et al. (2017).

that older patents have had more time to accumulate citations, and firm fixed effects to control for the presence of unobservable characteristics of the firms.

Table 2 Forward Citations and Patent Market Values, 1947:Q1- 2019:Q4

	(1)	(2)	(3)
Citations	0.253***	0.030***	0.121***
	(0.017)	(0.003)	(0.020)
Recession	-0.040	-0.086*	0.325
	(0.135)	(0.051)	(0.208)
Recession × Citations	-0.045	-0.013	-0.093*
	(0.050)	(0.014)	(0.052)
Observations	2,822,245	2,820,941	2,820,941
R^2	0.042	0.831	0.822
Grant Year FE	Y	Y	
Firm FE		Y	
Firm by Grant Year FE			Y

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We extend the sample of Kogan et al. (2017) that ended in 2010 to 2019, and confirm their finding of a positive association between forward citations and patent market values. However, as displayed in Table 2, we further establish that there is no strong statistical evidence that patent market valuations differ based on whether a patent is issued during a recession. Also, the relationship between forward citations and patent values is not significantly different based on whether the patent is issued in a recession.

3 Innovation Shocks and Aggregate Dynamics

To understand the effects of innovation activity on the economy, we conduct a comprehensive analysis of both average and state-dependent effects of innovation shocks at the aggregate and firm-level. We begin this section with an initial linear analysis using a long sample that dates back to the aftermath of World War II. This analysis largely confirms the findings of Cascaldi-Garcia and Vukotić (2022) and serves as a reference point for the more detailed analysis presented in the remainder of the paper.

We then evaluate the state-dependent aggregate effects of innovation shocks and highlight the importance of the non-linear analysis. Throughout this section, we explore the possibility that the effects of innovative activity may vary depending on the state of the economy. This assertion is grounded in the understanding that, although technological innovations require time for implementation, economic agents respond to the expected future potential of these innovations at the moment they are publicly disclosed. In addition, we draw on empirical evidence that connects the effects of technological shocks with the prevailing state of the economy.

Finally, we highlight the relevance of examining firm-level data to uncover specific firm characteristics that influence how innovation shocks are transmitted within the economy, with a focus on potential state dependencies.

3.1 Aggregate Effects of Patent-Based Innovation Shocks

We first establish a linear benchmark to assess the aggregate effects of expected future technological changes. To do this, we perform local projections (as in Jordà, 2005) employing patent-based innovation shocks with the specification

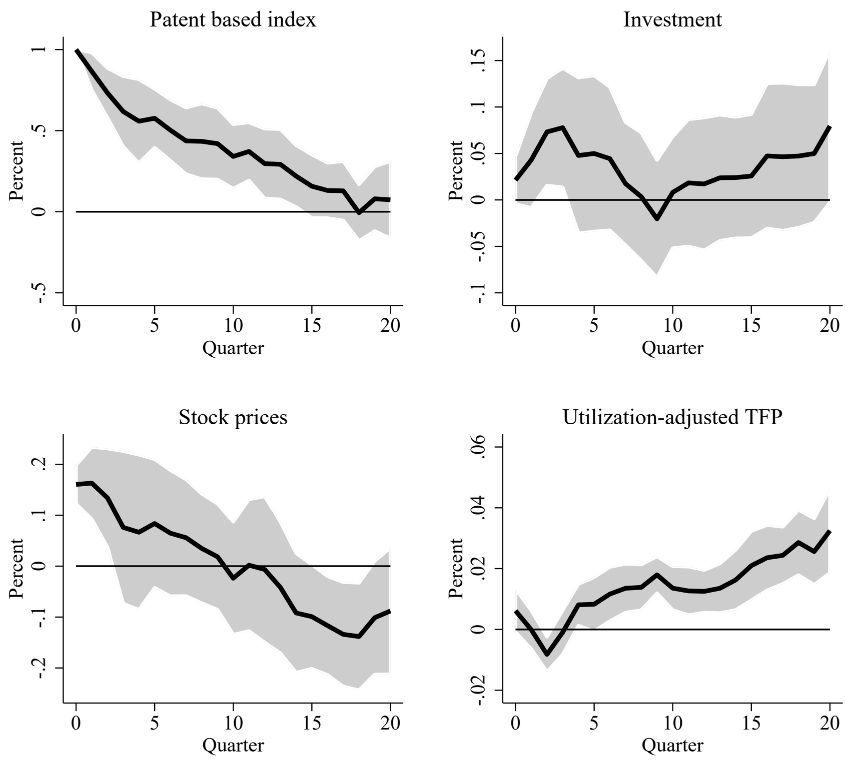
$$z_{t+h} = \alpha_h + \beta_h x_t + \psi_h(L) y_t + \varepsilon_{t+h}, \text{ for h = 0, 1, 2, ...,} \tag{2}$$

where z_t is our variable of interest, and x_t is the patent-based innovation index described above. We also consider a set of aggregate control variables that contain a combination of technology, real macroeconomic, and forward-looking variables. The controls are given by the vector y_t, including two lags of the patent-based innovation index, of utilization-adjusted TFP (constructed by Fernald, 2012), and other standard aggregate variables including real GDP, unemployment rate, T-bill rate, inflation, and the aggregate stock price index S&P500, as a forward-looking variable. We relegate the details about the aggregate variables and their sources to the Appendix A.3. The coefficient β_h on the innovation index represents the response of the variable z_t to an innovation shock at horizon h. This allows us to trace the impulse response of the variable of interest to the patent-based innovation shock. To account for the serial correlation induced by the Jordà method, we apply the Newey-West correction for standard errors (Newey and West, 1987). Our quarterly data covers the post World-War II period, from 1947:Q1 to 2019:Q4.

Figure 4 illustrates that a positive innovation shock leading to an increase in the aggregate patent-based innovation index results in higher aggregate investment and stock prices. Investment rises immediately, peaking approximately one year after the shock, exhibiting a hump-shaped pattern. Stock prices react instantaneously, with positive and significant effects for about three quarters after the shock. Interestingly, utilization-adjusted TFP, which serves as a proxy for the technological level of the economy, does not respond immediately, but rather shows a delayed reaction. The first positive and significant effect on TFP is observed roughly five quarters after the innovation shock.

Two main results emerge from these responses. First, the long delay between the shock to patent grants and the actual effect on productivity suggests that the innovation

Figure 4 Aggregate Analysis: Linear effects of patent-based innovation shocks



Note: Aggregate responses to patent-based innovations shocks. Corresponding 90% confidence bands shown.

shock encompasses the anticipated component of future technological changes.[8] Second, the observation that investment reacts before any increase in productivity indicates that firms react and adapt their plants based on the *expected* increase rather than tracking current productivity level. These results confirm the findings of Cascaldi-Garcia and Vukotić (2022) and provide evidence that stock market reactions to patent grants reflect anticipation of the markets regarding the future potential of patented technology and elicit an immediate reaction of investment ahead of these anticipated changes.

[8] We also explore a citation-weighted patent count measure based on forward citations of a patent that arguably captures scientific value and realization as opposed to anticipated potential of technological advancements. As shown in Appendix A.2.1, investment does not respond on impact to that measure. This further supports our view that we capture news about future technological changes with our market valuation based patent innovation index.

3.2 State-Dependent Aggregate Effects of Patent-Based Innovation Shocks

The rationale for studying state dependence arises from the inherent nature of innovation shocks. Technological innovations are often accompanied by adoption delays, meaning that agents respond not only to the immediate economic impact of the innovation but also to the expected future stream of outcomes that the innovation is anticipated to generate.

The state of the economy influences firms' strategic decisions, such as when to invest, expand, or hire, and also shapes their response to innovation shocks. For instance, if a firm learns that a new technology, like automation, will eventually boost productivity, it anticipates a positive return but must first adapt its production processes. This leads to an immediate need for investment before the technology is implemented, while potentially smoothing future revenues by spreading the costs over time.

A firm's ability and willingness to invest depend heavily on the economic conditions at the time they receive the news. During recessions, financially constrained firms may struggle to invest despite potentially stronger incentives to innovate, as innovation can offer growth opportunities (Segal, Shaliastovich, and Yaron, 2015). If credit is accessible, the economic impact of investment might be greater in recessions than in normal times. Additionally, factors such as state-dependent discount rates and financial constraints also play a role, along with hiring decisions.[9] Research (e.g., Caballero and Hammour, 1996) shows that unemployment costs are lower during recessions, influencing how firms respond to innovation shocks through hiring and firing decisions.

The combination of these individual firm-level investment decisions shape the aggregate outcome of the economy.[10] Below, we begin by examining these aggregate outcomes, investigating whether similar technological developments driven by patent grants lead to different reactions based on the state of the economy.

3.2.1 Responses of Key Variables

We expand the linear model from Equation (2) to a state-dependent setup, given by

$$z_{t+h} = I_{t-1}\left[\alpha_h^A + \psi_h^A(L)y_t + \beta_h^A x_t\right] + (1 - I_{t-1})\left[\alpha_h^B + \psi_h^B(L)y_t + \beta_h^B x_t\right] + \varepsilon_{t+h}, \qquad (3)$$

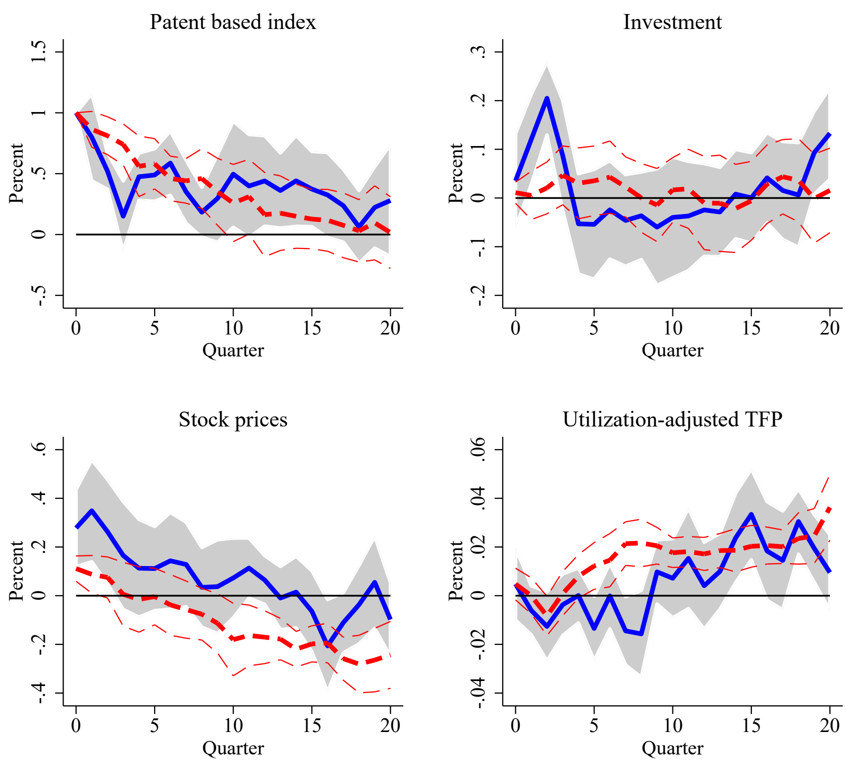
where $I_{t-1} \in \{0, 1\}$ is the state of the economy. We use a lagged state to deal with possible endogeneity concerns, so we address whether a shock propagates differently conditional on the state of the economy in the quarter before it hits. We define the state of the

[9] See Stachurski and Zhang (2021) for a review of the extensive literature on time-varying and state-dependent discount factors.

[10] Research on how these aggregate effects vary with state of the economy is limited. Some studies suggest that technological changes yield different outcomes depending on economic conditions. For instance, Cascaldi-Garcia and Galvão (2021) shows that technological improvements are linked to uncertainty, which rises during recessions.

economy by relying on NBER-dated recessions and normal times, assigning a value of 1 to the dummy variable during recessions and 0 otherwise. Here, β_h^k represents the response of variable z_t at horizon h in state $k \in [A, B]$ where A corresponds to recessions and B to normal times. This coefficient measures the average effect of the shock based on the initial state. We allow all coefficients to change based on the state of the economy, nesting the case of all coefficients being linear.

Figure 5 Aggregate Analysis: State-dependent effects of patent-based innovation shocks



Note: In recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown.

Figure 5 presents the state-dependent impulse responses after an innovation shock, comparable to the linear version presented in Figure 4. The blue solid lines represent the responses of stock prices, utilization-adjusted TFP, and investment to an innovation shock occurring during NBER-defined recessions, while the red dashed lines show the responses in normal times.

The comparison of the responses in recessions and normal times provides evidence of state-dependent effects of patent-based innovation shocks. Notably, for an identical 1% increase in the patent-based innovation index, we see a significantly large positive response of private investment on impact in recessions and an insignificant response in normal times. Stock prices rise in response to an innovation shock on impact in both states of the economy, and while point-wise this rise is larger in recessions, it is not statistically significantly different across the two states.

Utilization-adjusted TFP, a proxy for productivity stemming from technology, presents an interesting state-dependent behavior. Productivity reaches a new higher level in the medium to long run of about the same magnitude in both recessions and normal times, indicating that the 1% increase in the patent-based index is anticipating the same level of future productivity. However, during normal times, productivity starts to increase about one year after the innovation shock, substantially earlier than in recessions, that only sees significant gains in productivity about two and a half years after the shock. Still, the anticipation reaction through investment is remarkably larger in recessions than in normal times.

Considering the two opposing forces faced by the firm when deciding to invest during recessions, the empirical evidence of substantially higher investment during recessions favors a scenario where the benefit from exploring an opportunity to grow that originates from the innovation shock strictly dominates the burden of diminished access to credit or increased funding costs to finance this investment. The level of the firm's financial constraint may still play an important role on the investment decision and capacity to expand. We explore this particular characteristic when evaluating firm-level data in Section 4.[11]

Overall, we show empirical evidence that patent-based innovation shocks propagate differently through the economy during recessions compared to normal times, with a substantially higher impact on aggregate private investment during recessions.

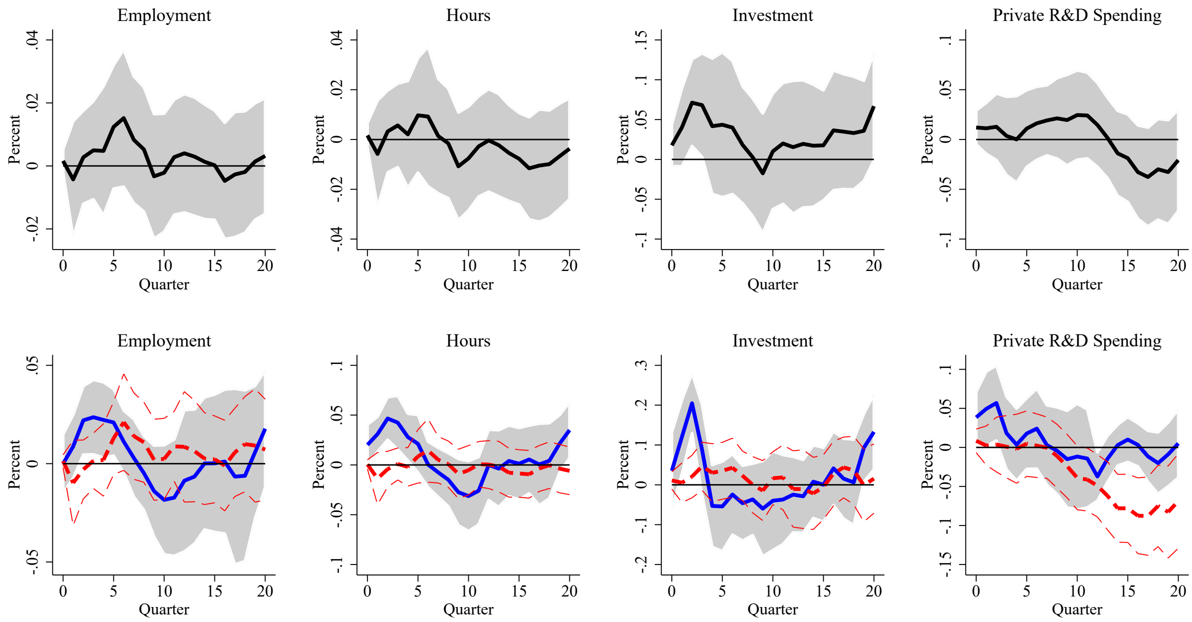
3.2.2 Re-balancing of Production Factors and the Role of R&D

We also consider the responses of additional variables related to firm-level decisions. Figure 6 shows the linear and state-dependent responses to patent-based innovation shocks for labor market variables, private investment (same as shown in Figures 4 and 5), and private R&D spending.

In the linear setup, both the extensive and intensive margins of the labor market (employment and hours, respectively) do not seem to react to the patent-based innovation shock. However, when analyzing the state-dependent results, both employment and hours worked react positively during recessions, mainly in the first five quarters after the shock. As in the linear case, during normal times, there is no significant effect on the labor market. While employment here is the net effect from hired new employees and potentially fired ones, the increase in employment during recessions suggests that new technologies

[11] Another aspect that may be behind the higher investment during recessions comes from a cleansing effect through creative destruction, where periods of crises crowd out less productive firms and positively selects more productive entrants (Caballero and Hammour, 1994, Foster, Haltiwanger, and Krizan, 2001, Akcigit and Kerr, 2018, and Ates and Saffie, 2021). While of merit, this angle has been already largely explored by the literature and is beyond the scope of this paper.

Figure 6 Aggregate Analysis: Effects of patent-based innovation shocks on additional variables



Note: The top row shows the response to patent-based innovation shock in the linear model and the bottom row shows the state-dependent responses, during recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown.

are demanding more workers, and that firms are taking advantage of the lower opportunity cost of unemployment and higher availability of unemployed skilled workers.

From a production factor perspective, during recessions, both labor (either through extensive or intensive margin) and capital (through investment) increase. However, the increase in investment is higher than observed in the labor variables, suggesting that, during recessions, the innovation shock induces a re-balancing from labor towards capital. While similar re-balancing can be observed in the linear setup, the state-dependent analysis indicate that this result stems primarily from recessionary periods.

Private R&D spending is the innovation-related component of private investment. Our results indicate that the average response of private R&D spending is insignificant in the linear setup. However, when we consider the state-dependent model, private R&D spending rises in recessions in response to an innovation shock on impact, but has an insignificant response in normal times. This suggests that the innovation shock, which signals expected future technology, leads to higher investment in development expenditures to make progress towards the adoption of the new technology, and thus help to explain the rise in TFP, with the development and implementation delay. We also explore this venue further when we consider firm-level data in Section 4.

3.2.3 Accounting for Monetary and Credit Conditions

A natural question that arises is whether our aggregate results about the differences between recessions and expansions are actually reflecting changes in other factors, such as the monetary stance or credit conditions. Both of these elements are potentially critical for understanding the private sector's response to aggregate innovation shocks.

In order to address these concerns, we include the 3-month T-bill rate in our baseline analysis as a control variable, given by the vector y_t in Equations (2) and (3) for the linear and state-dependent cases, respectively. This helps to capture the changes in the monetary stance. Also, when we consider the response of the T-bill rate to a patent-based innovation shock, we see that it has no statistically significant response on average (see Figure A.2) or across states of the economy (see Figure A.3). Therefore, the monetary response does not seem to play a role in propagating differences across recessions and expansions.

In order to assess the role of credit conditions, we measure the relationship between the patent-based innovation index and BAA-AAA corporate spread, which is a commonly used indicator of credit conditions.[12] The correlation between the two is negligible, at 0.08. In order to control for credit conditions, we also add this variable to the set of controls, given by the vector y_t in Equations (2) and (3) for the linear and state-dependent cases, respectively. We find that our baseline results are robust to the inclusion of credit supply conditions, and responses of TFP, stock prices and private investment are essentially unchanged. We also consider the response of the BAA-AAA corporate spread to a patent-based innovation shock. In the linear specification, it falls on impact and rises in the medium run, consistent with earlier evidence from Cascaldi-Garcia and Vukotić (2022). Notably, the response of this credit measure is not statistically significantly different across recessions and normal times. These responses are shown in Appendix Figure A.4.

4 Innovation Shocks and Firm-Level Dynamics

The aggregate results of our analysis reveal state-dependence in response to patent-based innovation shocks, driven by the asymmetric response of private investment. In this section, we examine firm-level variables, including firm investment decisions, to explore how they respond to aggregate innovation shocks and whether these responses differ during good and bad economic times.

[12]The other commonly used measures of credit conditions, the excess bond premium and the Gilchrist and Zakrajšek (2012) credit spread are available for a much shorter sample from 1973 onwards than our baseline sample starting in 1947. However, the BAA-AAA corporate spread is available for a much longer sample, spanning our sample under consideration, and is positively correlated with these other two measures for overlapping sample.

In our analysis, we rely on quarterly data from the Compustat database, which provides detailed balance-sheet and income-statement information for all publicly traded U.S. firms over a long horizon. Our analysis focuses on key variables that are likely to be impacted by changes in patent-related innovations, such as firm-level capital accumulation (constructed using the perpetual inventory method), sales, output (measured as sales plus the change in inventory), and R&D spending. Additionally, we consider various firm characteristics that may explain the response to these shocks, including leverage, liquidity, dividends paid, firm size, firm age, and distance to default. Appendix A.4 provides detailed information on the construction of these variables. Our baseline sample covers the period from 1966:Q1 to 2019:Q4.[13]

The use of the Compustat database in our analysis has several advantages. First, it provides a long sample period and covers a large number of firms, making it suitable for conducting robust empirical analyses. Additionally, since our patent-based innovation index is based on the stock market valuations of publicly traded firms, using Compustat allows us to capture the effects of innovation shocks on these firms. Although companies covered by Compustat account for 60 percent of total investment in the U.S., they are representative of the aggregate investment dynamics as highlighted by Cloyne et al. (2023). Therefore, by utilizing Compustat database, we can gain valuable insights into how innovation shocks impact publicly traded firms and contribute to our understanding of the broader implications for aggregate investment.

4.1 Firm-Level Effects of Patent-Based Innovation Shocks

In order to obtain the average response of firm-level variables to an aggregate patent innovation shock, we consider the specification

$$z_{jt+h} = \alpha_{jh} + \alpha_{sth} + \beta_h x_t + \psi_h(L) y_t + \Gamma_h F_{jt-1} + \varepsilon_{jt+h} \tag{4}$$

where α_j is a firm j fixed effect and α_{st} is a sector s by quarter t fixed effect. Note that the firm fixed effects capture broad differences in the firm-level variables across firms, including investment decisions, sales, and profits. The sector-by-quarter fixed effects help to capture any sector-specific exposure to aggregate shocks.[14] Once again, x_t is the patent-based innovation index, and the coefficient β_h gives the response of the variables of interest z_{jt} to an innovation shock. Here y_t is a vector of controls comprising of two

[13] The availability of data for different firm-level variables vary. For example, data for R&D spending is regularly available in the sample from mid to late 1980s. We also show in Figure A.5 that our aggregate results are also robust for this sub-sample.

[14] This specification is similar to Ottonello and Winberry (2020), and we also define the sectors s similarly based on SIC codes, and include agriculture, forestry, and fishing; mining; construction; manufacturing; transportation communications, electric, gas, and sanitary services; wholesale trade; retail trade; and services. We exclude finance, insurance and real estate, and utilities sectors from our data set.

lags of the aggregate-level variables from our aggregate specification. In addition, we also consider control variables at the firm-level in the vector F_{jt}, which include sales growth of the firm and current assets as a share of total assets. In the next section, we also consider other balance sheet variables such as leverage, liquidity, and size based on assets. We cluster standard errors in two ways to account for correlation within firms and within quarters.[15]

The left panel of Figure 7 shows the average response of selected firm-level variables to the aggregate patent-based innovation shock. In response to this shock, firm-level investment in tangible capital increases mildly about six quarters after the shock hits the economy. This finding is consistent with macroeconomic models with technological news shocks, which predict a rise in capital investment by firms to increase their productive capacity for the arrival of the new technology.

We observe that the inventories-to-sales ratio declines on impact as firms reduce their inventories relative to sales when the shock occurs. This result aligns with Vukotić (2019), who finds that the inventories-to-sales ratio in the manufacturing sector falls ahead of future technological improvements. Similarly, Görtz, Gunn, and Lubik (2022a) show that while inventory levels increase in response to news shocks, the inventories-to-sales ratio behaves countercyclically.[16]

Aggregate models also predict a rise in consumption in response to anticipated technological advancements, and consistent with that, we find a surge in firm-level sales, output (which is the sum of sales and changes in inventories), and profit in response to our innovation shock.[17] In addition to tangible capital, our analysis also indicates that firms increase investment in non-tangible capital, such as research and development spending (R&D) and selling, general, and administrative expenses (SG&A), as shown in the bottom-left panels of Figure 7.

To test whether firm-level variables have different responses to aggregate patent innovation shocks in recessions versus normal times, we use the specification

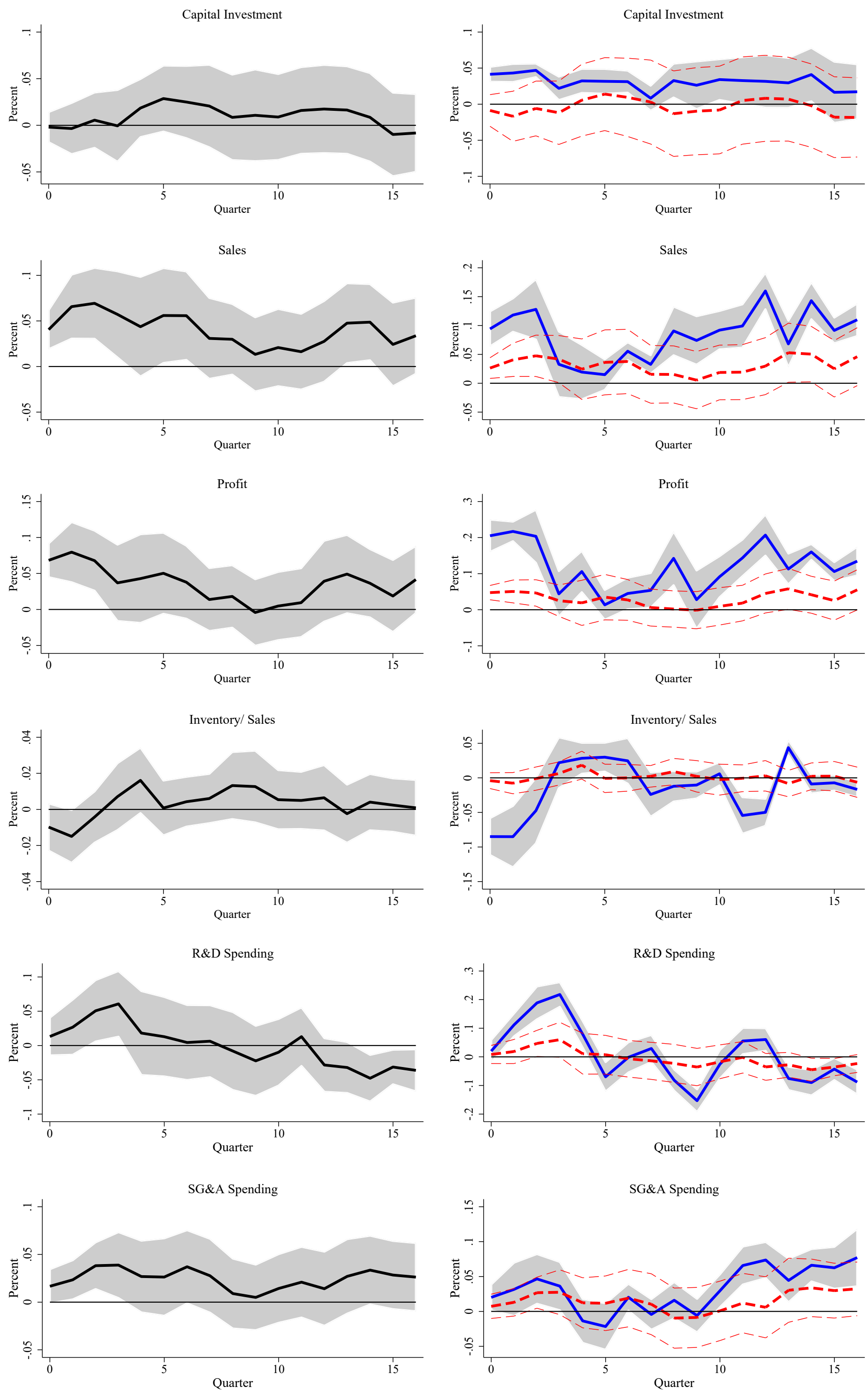
$$z_{jt+h} = \alpha_{jh} + \alpha_{sth} + I_{t-1}\left[\beta_h^A x_t + \psi_h^A(L)y_t\right] + (1 - I_{t-1})\left[\beta_h^B x_t + \psi_h^B(L)y_t\right] + \Gamma_h F_{jt-1} + \varepsilon_{jt+h}, \tag{5}$$

[15] For some state-dependent analysis, we depart from this double-clustering when our sample size under consideration becomes smaller.

[16] Although we do not present the results on inventory levels, we also find that they rise, but at a slower pace than sales, leading to a decline in the inventories-to-sales ratio. Crouzet and Oh (2016) impose structural restrictions on the comovement between inventories and sales in a theoretical model and suggest that sales increase in response to news of future productivity gains, while inventories decline as firms choose to deplete their current stock rather than increase production, anticipating that future production will be cheaper. Their work is thus not directly comparable. However, their model also predicts a fall in inventory-to-sales ratio, consistent with our empirical findings.

[17] When we consider the response of aggregate variables to a patent-based innovation shock, we also document a rise in consumption of non-durables in response to the shock, as shown in Figure A.3 in the Appendix. Other components of consumption have a more muted response.

Figure 7 Firm-level Analysis: Average effects of patent-based innovation shocks (left) and state-dependent (right)



Note: Left panels present linear results and right panels present state-dependent results, with recessions in blue and normal times in red. Corresponding 90% confidence bands shown.

where $I_t \in \{0, 1\}$ indicates the state of the economy, taking a value of 1 in recessions and 0 otherwise. All other variables are defined similarly as in Equation 4.

The right panel of Figure 7 shows the responses of the firm-level variables to the aggregate patent-based innovation shock in recessions (solid blue) and normal times (red dashed). In response to this innovation shock, firm-level capital investment increases significantly more during recessions than in normal times. Moreover, capital investment initially rises in bad economic times, and the increase is persistent and statistically significant when the innovation shock occurs during a recession. This difference in the firm-level capital investment response across economic conditions mirrors our aggregate results for private investment, indicating that the aggregate state-dependence is likely rooted in the firm-level investment decisions.

We also observe that sales, and consequentially profits, rise more in recessions than in normal times on impact. Furthermore, sales and profits tend to pick up even more down the road after the technology has been implemented and utilized, particularly when the shock occurs during a recession, indicating a delayed but larger response of sales to the innovation shocks that originate in challenging recessionary times. The inventories-to-sales ratio falls both during normal and recessionary times, but this fall is greater when the innovation shock hits in a recession.

Taken together, the empirical evidence presented in Figure 7 emphasizes that innovation shocks that occur in bad times come with an opportunity for growth that requires rapid production adaptations. This includes not only leading firms to invest in modernization of their production facilities but also creating a greater incentive to sell their current products and increase inventories at a rate slower than sales, stemming from potentially older technology.

Turning to the bottom-right panels of Figure 7, and the responses of intangible capital investment, we observe an interesting and clear difference in how R&D and SG&A spending respond in good and bad times. While both SG&A and R&D spending are categorized as intangible capital, R&D represents innovation-related spending and SG&A is often linked to broader operational or non-innovation-related activities. The trade-offs and substitution effects across these two types of spending are more salient when an innovation shock occurs during a recession. Specifically, in a recession, there is a rise in R&D and in SG&A spending in response to the shock, while these increases are statistically insignificant during normal times. SG&A spending, however, increases by far less than R&D, with the bulk of the effect occurring many quarters after the shock, suggesting that firms hold off on administrative capital spending in recessions.[18]

As R&D is viewed as a major source of economic growth, understanding its behavior in the immediate aftermath of innovation shocks is key. As shown in Section 2.1, ag-

[18] It is worth noting that while SG&A spending data spans a longer part of the sample, R&D spending data becomes more widely available across firms starting in the mid to late 1980s.

gregate R&D spending data is unconditionally procyclical, and several researchers have attempted to provide theoretical explanations for such procyclicality.[19] Our findings, however, show that R&D reacts more strongly during recessions than in normal times, providing empirical support for the Schumpeterian notion that recessions are opportune times for investing in relatively cheaper, growth-enhancing activities, but in a conditional sense. Our empirical results align with the theoretical work of Shleifer (1986) and Francois and Lloyd-Ellis (2003), who posit that firms develop ideas during recessions by investing in R&D and wait to implement them during economic booms when profits are higher. Receiving positive news about a patent grant during a recession provides firms with additional time to engage in R&D activities when opportunity costs may be lower, allowing them to bring the developed idea to market when aggregate economic conditions have improved.

In summary, we provide rich firm-level evidence on the response of firm decisions to aggregate innovation shocks. In particular, we show that the response of firm capital investment is larger in recessions than in normal times, which is consistent with the response of aggregate private investment. In the following section, we explore the factors that influence the transmission of innovation shocks.

4.2 Firm Characteristics: Industry and Patenting Activity

The previous section provides the average firm-level response to the aggregate patent-based innovation shock. However, patenting activity is conducted by a relatively small share of firms in our sample, approximately 20%.[20] This activity is highly concentrated in the manufacturing sector, which accounts for about 85% of total patents. The services sector follows at a distant second, with roughly 8% of patenting firms.[21] Other industries represent only small shares of patenting activity. It is worth noting, however, that this distribution broadly aligns with the composition of publicly listed firms within Compustat.[22]

This raises the question of which firms are driving the average response to aggregate innovation shocks, both over the full sample period and when comparing recessions to normal times. We begin by focusing on patenting versus non-patenting firms. We conduct

[19] For example, Barlevy (2007) develops a model where firms have the incentive to undertake R&D activities in booms when profits are higher, shedding light on this observed pattern. This theory, however, assumes that results of R&D activities can be put to practical use without delay.

[20] This is when we consider a merged dataset of Compustat with CRSP, and after the standard trimming steps are applied.

[21] The notable manufacturing sub-sectors with patenting are Electronic and other Electrical Equipment and Components and Industrial and Commercial Machinery and Computer Equipment. The notable services sub-sector with patenting is Business Services, with Computer Programming as a predominant sector with innovation.

[22] Around 50% of the firms sampled in Compustat are manufacturing firms, about 20% in services, around 6% in mining and transportation respectively, and smaller shares for the rest.

the analysis in Equations (4) and (5) separately for firms which have patented at any point within the sample, and for those firms which have never patented. The top two panels of Figure 8 show the response of capital investment for both sets of firms to the aggregate patent-based innovation shock. The left side column shows that capital investment rises in response to an aggregate shock for both types of firms. The right column shows that there is evidence of state-dependence for both types of firms, and both patenting and non-patenting firms tend to increase capital investment in recessions in response to an aggregate based innovation shock. This suggests that the transmission of technological news shocks is broader and extends beyond innovation-intensive firms engaged in significant R&D and patenting activity.

We also conduct a similar analysis by focusing on firms in a specific industry. The bottom two panels of Figure 8 show the response of capital investment to an aggregate patent innovation shock for firms in the manufacturing sector (third row) and the service sector (bottom row). Investment goes up in both manufacturing and services sector in response to the shock, particularly during recessions, where the rise is more persistent in manufacturing relative to services. The increase in investment in the services sector, which is less innovation-intensive than manufacturing, brings additional evidence of the aggregate spillovers of the innovation shock.[23]

The main takeaway here is that the effects of innovation shocks extend beyond specific firms or sectors, with significant spillovers across industries. This could be due to the nature of technological advancements, input-output linkages in the production network, or direct competition. Both patenting and non-patenting firms show notable responses, highlighting that technological advancements impact the broader economy. This broad-based impact underscores the importance of considering the economy-wide effects of technological progress, as innovations do not merely benefit or affect decisions of R&D-intensive or patenting firms but have far-reaching implications for overall economic activity.

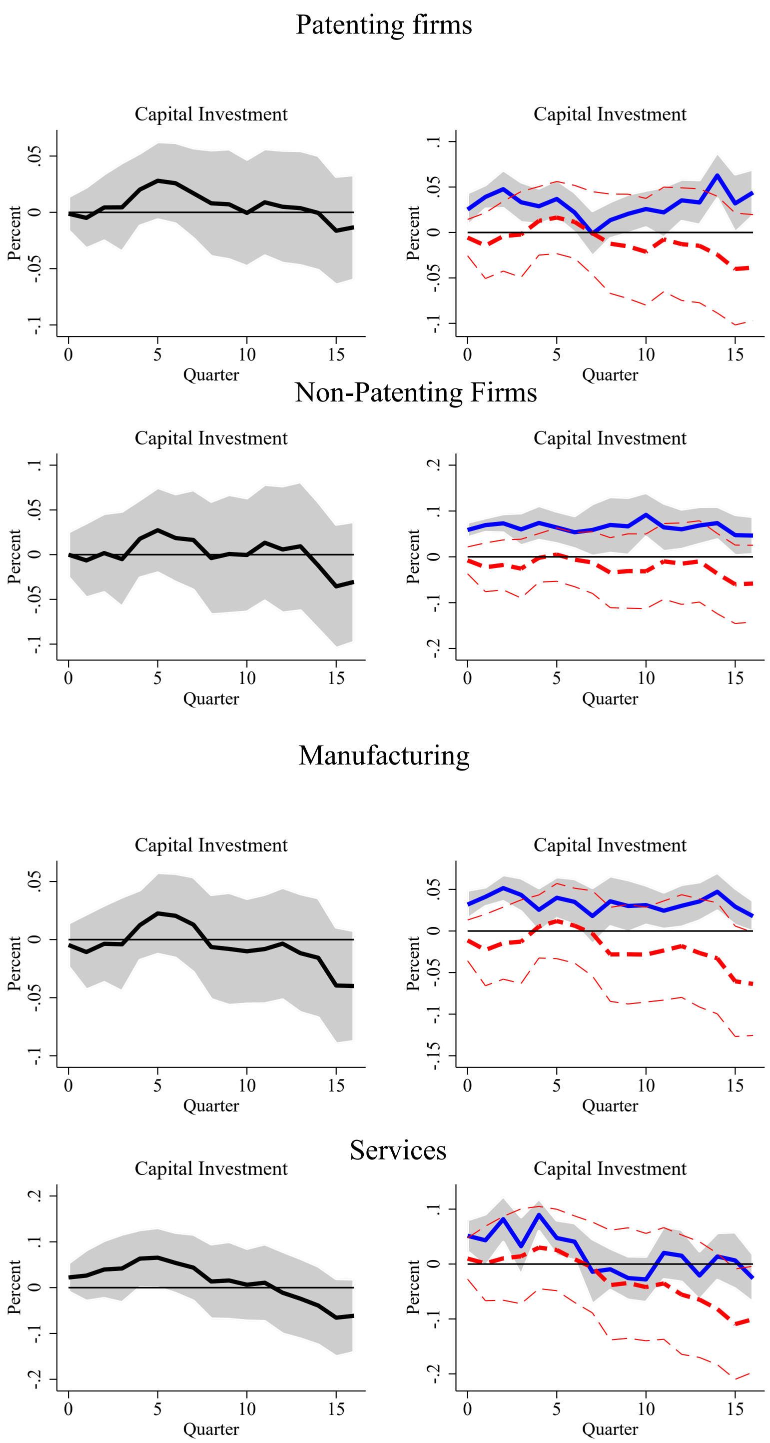
4.3 Firm Characteristics: Role of Financial Constraints

In this section, we conduct a detailed analysis of firm characteristics in order to understand the factors driving the response of firm investment to aggregate innovation shocks on average, and also across good and bad times.

Drawing on the literature highlighting the role of financial constraints in the transmission of macroeconomic shocks, we examine how financial frictions shape firms' investment behavior in response to innovation shocks. Specifically, we explore how firms with varying levels of financial health respond to these shocks and how economic conditions affect

[23]The responses across other industries including retail and wholesale are similar for the state dependent responses point-wise, but given the fewer observations among the sample under consideration, the responses are not statistically significant.

Figure 8 Firm-level Analysis: Effects of patent-based innovation shocks (left) and state-dependent (right) based on patenting activity and sector



Note: Left panels present linear results and right panels present state-dependent results, with recessions in blue and normal times in red. Corresponding 90% confidence bands shown.

these responses, using multiple measures of financial friction to gain deeper insight. Evidence from the previous section shows that on average firms increase capital investment in response to favorable innovation shocks during recessions. However, heterogeneity in firms' financial positions may mask important differences in their ability to respond, with financially constrained firms potentially unable to pursue these investment opportunities.

We consider four measures of financial constraints to investigate this transmission channel—liquidity, leverage, distance to default, and firm size—capturing different aspects of a firm's financial health. Liquidity measures the firm's ability to meet short-term financial obligations and has been highlighted as an important transmission mechanism by Jeenas (2019). Leverage, measured as the debt-to-asset ratio, reflects the extent to which a firm relies on debt financing. distance to default is a measure of credit risk that estimates the probability of default based on a structural credit risk model proposed by Merton (1974). This model incorporates two key components: a firm's equity value, which captures market expectations, and the face value of its debt, which defines the default threshold. The size of the firm, measured by total assets, has been used as a traditional (but imperfect) proxy for financial constraints since Gertler and Gilchrist (1994), given that smaller firms are generally more financially constrained than larger ones.[24]

4.3.1 Exploring Within-Firm Variation

In order to assess the role of the various measures of financial constraint, we estimate the following specification

$$z_{jt+h} = \alpha_{jh} + \alpha_{sth} + \gamma_h(f_{j,t-1} - E[f_{jt}])x_t + \psi_h(L)y_t + \Gamma_h F_{jt-1} + \varepsilon_{j,t+h}. \tag{6}$$

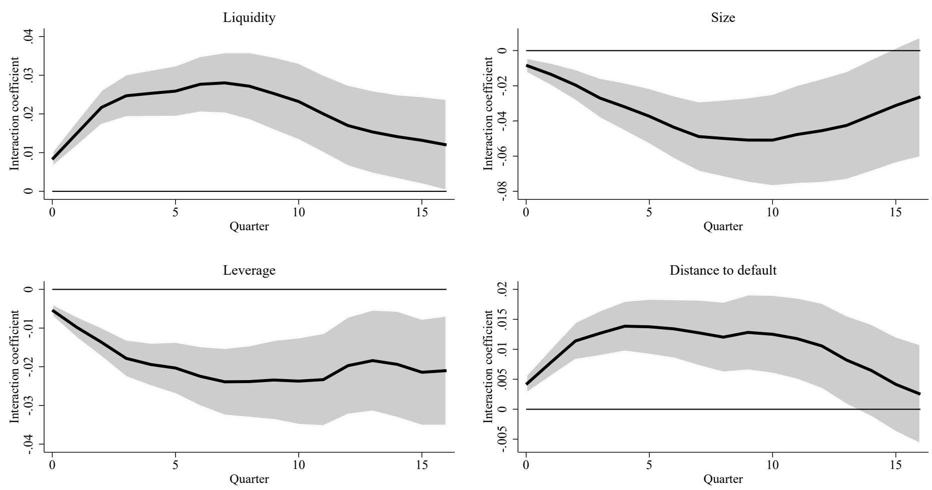
Here z_{jt} represents firm-level capital investment, x_t is the patent-based innovation index, and y_t includes aggregate-level control variables. For each firm characteristic f_{jt}, we consider $(f_{j,t-1} - E[f_{jt}])$, the deviation of the firm characteristic from the average of f_{jt} for firm j in the sample, then standardize it over the entire sample. This approach captures within-firm variation in the variable of interest, similar to Ottonello and Winberry (2020). By demeaning the characteristics within firms, our estimates reflect how a firm responds to the shock when the given characteristic is higher or lower than usual. In contrast, if we interacted the firm characteristic with the shock, our results would partly be influenced

[24] Leverage is measured as the debt-to-asset ratio, calculated as the sum of short-term and long-term debt divided by the book value of assets. distance to default in addition to leverage is a measure recently used by Ottonello and Winberry (2020), following the work of Gilchrist and Zakrajšek (2012) and Schaefer and Strebulaev (2008). The probability of default is constructed using the market value of equity, the volatility of equity, and the face value of the firm's debt. The equity volatility is estimated using historical daily stock returns from CRSP using a 250-day rolling window. The face value of debt is approximated with the sum of the firm's current liabilities and one-half of its long-term liabilities, as the latter requires only the coupon payment. The estimation procedure is explained at length in Gilchrist and Zakrajšek (2012).

by permanent differences in responsiveness across firms based on those characteristics. Given that we are considering responses to innovation shocks, we abstract from potential fundamental differences between innovating and non-innovating firms, assumption which we relax in the following section. Our analysis uses firm-level data from 1984 onward, constrained primarily by the availability of distance to default measure. This sample period also aligns with previous studies such as Cloyne et al. (2023) and Ottonello and Winberry (2020), who analyze the transmission of monetary policy shocks.

The firm-level controls, given by F_{jt}, include variables such as sales growth and current assets as a share of total assets, along with the firm-level characteristic under consideration, and an interaction of the firm-level characteristic with GDP in order to capture cyclical sensitivities, as discussed in Section 2.1.

Figure 9 Capital investment response based on firm characteristics



Note: Average dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks. Corresponding 90% confidence bands shown.

We first investigate how capital investment responds depending on the firm's financial position and size. Figure 9 shows the coefficient on the patent innovation index interacted with the standardized firm characteristic under consideration.[25] The upper-left panel of the figure suggests that a firm has a higher semi-elasticity of investment to a patent-based innovation shock when it is one standard deviation above its typical level of liquidity. The bottom-left panel shows that when firms have higher than average leverage, they exhibit a lower responsiveness of investment to innovation shocks. The bottom right panel indicates that when firms have an above-average distance to default, they exhibit a stronger response of investment to innovation shocks. Taking together, these results suggest that firms that are less financially constrained, i.e., with high liquidity, high

[25] The results shown in Figures 9 and 10 hold qualitatively and quantitatively for the firm characteristics for the full sample starting in 1966, where information is available for liquidity, leverage and firm size. These are shown in Figure A.9 in the Appendix.

distance to default, and low leverage, are more responsive to innovation shocks, and the shocks propagate through higher investment responses.

The result for firm size, on the upper-right panel, suggests that when firms have below average assets, they respond with larger capital investment. This result should be read with caution as, while smaller firms are indeed more financially constrained than larger,[26] these are also the fastest growing firms. In addition, recent evidence from Crouzet and Mehrotra (2020) shows that investment in small firms tends to be more sensitive to the business cycle than in large firms. So, if on the one hand financial constraints hinder the potential investment expansion of smaller firms, on the other hand, the larger sensitivity to shocks favors it. The result shown in the upper-right panel of Figure 9, with lower capital investment response when the firm has more assets, indicates that the larger sensitivity channel dominates the financial constraint when analyzing the response based on firm size.[27]

Next, we consider if these firm characteristics that serve as proxies for financial constraints also play a role in explaining our firm-level state-dependent results. As before, we extend the analysis described by Equation (6) to a state-dependent form, as in

$$\begin{aligned} z_{jt+h} = \alpha_{jh} + \alpha_{sth} + I_{t-1}[\gamma_h^A (f_{j,t-1} - E[f_{jt}])x_t + \psi_h^A(L)y_t] \\ +(1 - I_{t-1})[\gamma_h^B (f_{j,t-1} - E[f_{jt}])x_t + \psi_h^B(L)y_t] + \Gamma_h F_{jt-1} + \varepsilon_{j,t+h}, \end{aligned} \tag{7}$$

where $I_t \in \{0, 1\}$ indicates the state of the economy, taking a value of 1 in recessions and 0 in normal times.

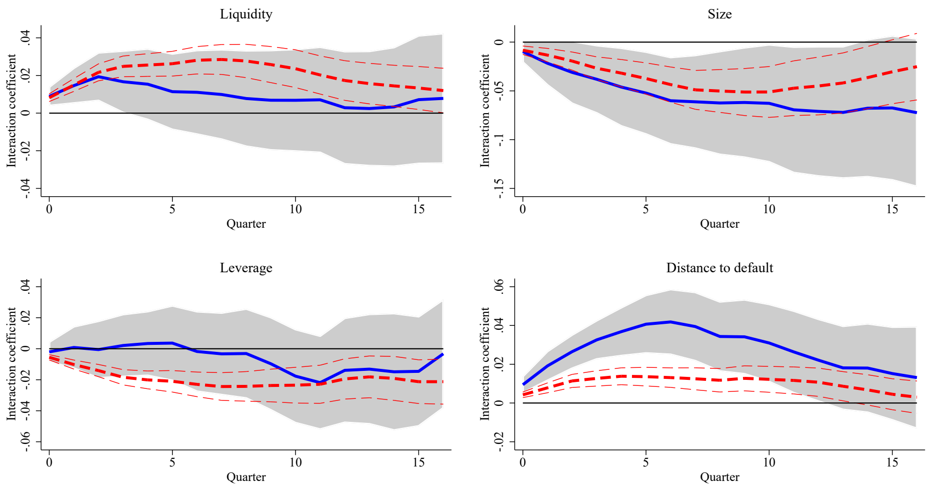
As shown in the right panels of Figure 10, firm leverage and liquidity do not play statistically different roles in explaining investment responses across recessions and normal times. However, this is not the case when we consider distance to default, where the response of capital investment is even more pronounced during recessions for the less financially constrained, as presented by the bottom-right panel of Figure 10. Specifically, during economic downturns, firms with higher distance to default exhibit a stronger response to favorable innovation shocks, increasing their capital investment to a larger extent. This result suggests that firms in stronger financial positions are better positioned to take advantage of innovation opportunities during recessions.

Overall, firm characteristics like liquidity, leverage, and distance to default are highly correlated, as shown in Table A.2 in the Appendix. The fact that distance to default helps explain the difference in the firm investment response across the states of the economy,

[26] Size has a positive correlation with other financial constraint measures, as shown in Table A.2 in the Appendix.

[27] The results are robust to alternative definitions of variables. Figure A.10 in the Appendix shows that we get very similar results when we consider net leverage, which is total debt net of total assets, and also consider an alternative definition of size based on firm sales instead of firm assets. Notably, we consider a size measure based on Gertler and Gilchrist (1994) which identifies a small firm if its average sales over the past 10 years is below the 30th percentile of the distribution.

Figure 10 STATE-DEPENDENT CAPITAL INVESTMENT RESPONSE BASED ON THE FIRM CHARACTERISTICS



Note: State-dependent dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks. In recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown.

above and beyond other characteristics such as liquidity and leverage, is not surprising. distance to default measures the probability of firm default over the near-term horizon, and as shown by Farre-Mensa and Ljungqvist (2016), it does a far superior job than these other proxies in capturing a firms' ability to borrow, and thus finance investment. The role of borrowing ability is particularly critical and amplified during recessions, when liquidity and credit supply are generally scarce. The result of higher capital investment response for less financially constrained firms indicates that, whenever positive innovation shocks occur during recessions, there is a pent-up appetite for investment expansion that is curtailed by credit constraints.

Finally, the upper-right panel of Figure 10 also indicates no statistical difference between investment response in recessions and normal times when controlling for firm size. Considering that recessions are indeed periods of higher financial constraint than normal times, the similar responses confirm the hypothesis that it is the larger sensitivity to shocks of small firms' investment that is driving the overall effect, and not the fact that smaller firms are more financially constrained than larger.

4.3.2 Exploring Across-Firm Variation

In departure from the analysis above where we have considered within-firm variation, we also consider across-firm variation. We modify Equation (6) to consider the deviation of the relevant firm characteristic from its average across *all* firms, in the following way,

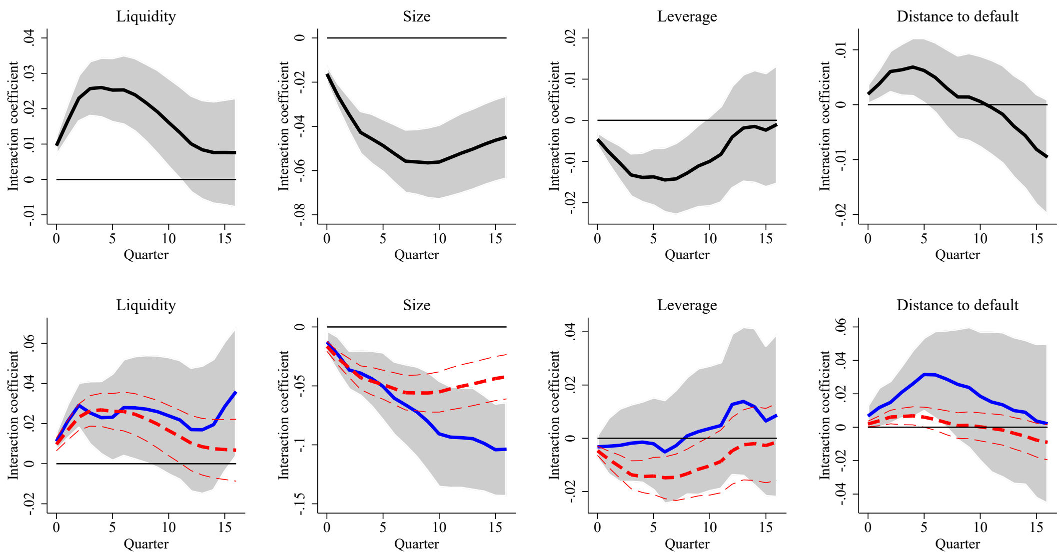
$$z_{jt+h} = \alpha_{jh} + \alpha_{sth} + \gamma_h(f_{j,t-1} - E[f_t])x_t + \psi_h(L)y_t + \Gamma_h F_{jt-1} + \varepsilon_{j,t+h}. \tag{8}$$

Analogously, Equation 7 considering state-dependent effects is modified as follows:

$$\begin{aligned} z_{jt+h} = \alpha_{jh} + \alpha_{sth} + I_{t-1}[\gamma_h^A(f_{j,t-1} - E[f_t])x_t + \psi_h^A(L)y_t] \\ +(1 - I_{t-1})[\gamma_h^B(f_{j,t-1} - E[f_t])x_t + \psi_h^B(L)y_t] + \Gamma_h F_{jt-1} + \varepsilon_{j,t+h}, \end{aligned} \tag{9}$$

where $I_t \in \{0, 1\}$ indicates the state of the economy, taking a value of 1 in recessions and 0 in normal times.

Figure 11 Average and state-dependent capital investment response based on the firm characteristics: Across firm analysis



Note: Average (top row) and state-dependent (bottom row) dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks. In recessions (blue solid) and normal times (red dashed), for sample period spanning 1984-2019. Corresponding 90% confidence bands shown.

We obtain very similar results with these specifications, and the linear and state-dependent results are shown in Figure 11. When we consider across-firm variation, the capital investment response is larger for firms with higher liquidity and distance to default and lower size and leverage, relative to the average across the entire sample. The magnitude and the dynamic effects are slightly different from the ones shown in Figure 9. Notably, these firm characteristics are relatively more important for the short-run response of capital investment to a patent-based innovation shock. The state-dependent responses also look similar to the within-firm analysis, with distance to default explaining the difference in the investment response of firms across recessions and normal times.

4.3.3 Equity-Constrained versus Debt-Constrained Firms

Having established that financial constraints play a critical role in shaping firms' responses to innovation shocks, we now distinguish between constraints in equity versus debt financing. This distinction is crucial since a firm's distance to default depends on both components, each potentially limiting the firms' ability to adapt to these shocks in different ways.

We use financial constraint measures from Linn and Weagley (2023). They train a random forest model, using the financial constraint classifications developed by Hoberg and Maksimovic (2014), based on the textual analysis of firms' 10-K filings, with a particular focus on liquidity discussions in the Management's Discussion and Analysis section.[28] Their model predicts financial constraints for all firms in the sample, with separate measures for firms reporting equity and debt financing issues. These measures are particularly valuable because they offer a comparable metric to earlier methods, while extending the coverage to a longer time period and a larger set of firms.

The resulting measures are standardized within each year, indicating that firms with higher index values in a given year are considered more financially constrained relative to others, based on either equity or debt issuance. This standardization makes it particularly suitable for exploring the variation across firms and for examining how different types of financial constraints influence variations in firm investment behavior.[29]

We interact this firm-specific measure with the innovation shock to capture its marginal impact on firms' investment and financing decisions in both linear and state-dependent settings, following the same approach as in Equations (8) and (9). The firm-level controls in the equation remain unchanged from our previous analysis. The sample period begins in the first quarter of 1972 due to the availability of debt and equity constraints data.

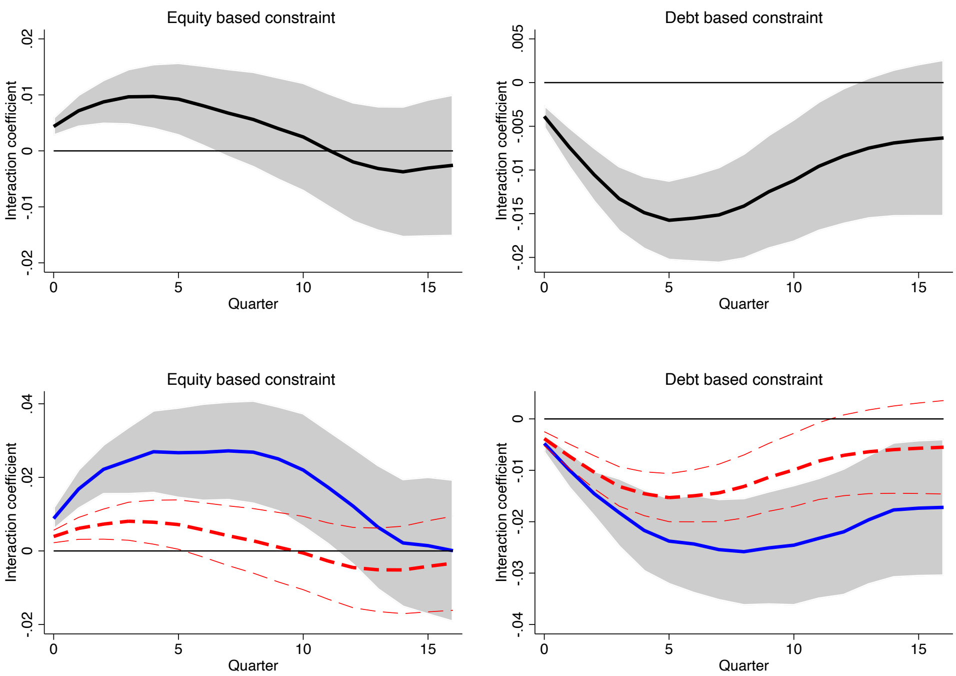
We first examine how financial constraints affect firms' investment responses to innovation shocks. Figure 12 shows that equity-constrained firms significantly increase their investment following an innovation shock, with this effect amplified during recessions. In contrast, debt-constrained firms reduce their investment, especially during economic downturns. We examine why equity- and debt-constrained firms respond differently to innovation shocks by analyzing their distinctive characteristics.

Debt-constrained firms typically have higher leverage, as shown in Table A.3 with correlations across firm characteristics. Thus, these higher debt levels likely limit their ability to raise additional financing, preventing them from increasing investment in response to innovation shocks. These effects seem to be present throughout the business

[28] The classifications capture four distinct sources of liquidity challenges: broad, debt-related, equity-related, and private placement financing. They identify the complex, non-linear relationships between accounting variables and the text-based constraint classifications, with a focus on debt- and equity-related constraints.

[29] We interpolate the annual data to quarterly frequency, which is reasonable given that these financial constraints typically remain stable over short periods.

Figure 12 State-dependent capital investment response based on the firm characteristics



Note: Dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks, both linear (top panel) and non-linear (bottom panel). Recessions are indicated by solid blue lines, and normal times by dashed red lines. Corresponding 90% confidence bands shown.

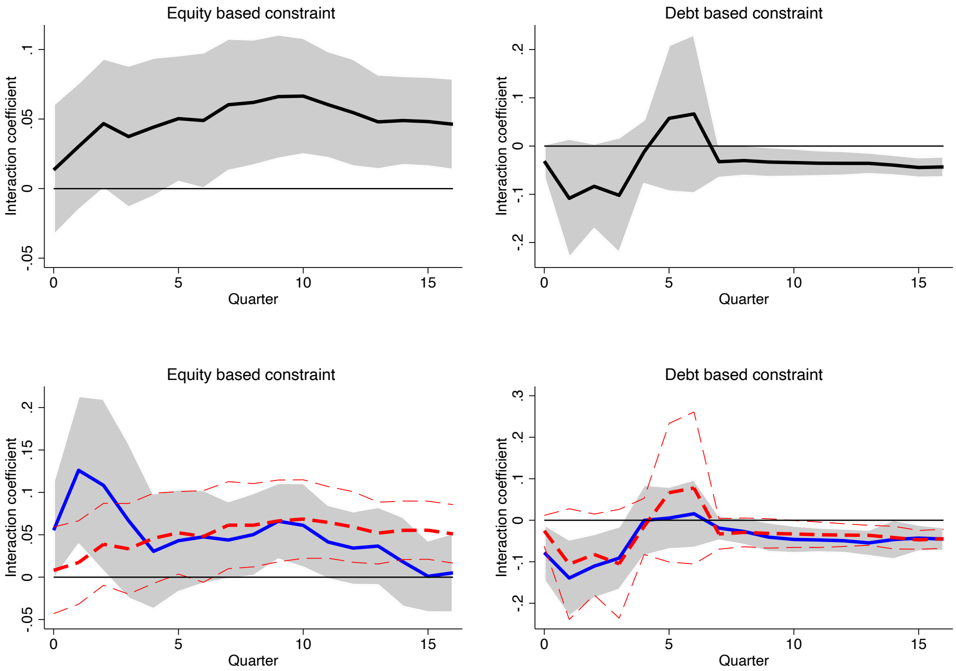
cycle but become more pronounced during recessions.

In contrast, equity-constrained firms are typically more R&D-intensive and operate in sectors where R&D investment is prevalent, as emphasized by Hoberg and Maksimovic (2014). Table A.3 confirms this pattern, showing a high positive correlation between equity constraints and R&D intensity (measured by the R&D to sales ratio).[30] Additionally, these firms often demonstrate greater innovation potential. However, these R&D intensive firms may face challenges in securing equity financing due to information asymmetry, the need to protect proprietary information, and the risk-averse tendencies of equity markets.

We posit that favorable innovation shocks arising from news about patent grants are particularly beneficial for these firms, helping to alleviate financial constraints, partially due to the public disclosure of relevant innovation information. Our objective is to identify potential sources that can ease these constraints and support an increase in investment. To achieve this, we analyze multiple financial variables, starting with Tobin's q—the ratio

[30]These firms also tend to maintain higher liquidity and lower leverage compared to their debt-constrained counterparts, as reflected in Table A.3.

Figure 13 State-dependent response of Tobin's q based on the firm characteristics



Note: Dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks, both linear (top panel) and non-linear (bottom panel). Recessions are indicated by solid blue lines, and normal times by dashed red lines. Corresponding 90% confidence bands shown.

of a firm's market value to its assets' replacement cost.[31] This ratio serves as an indicator of the value of potential investments.

Figure 13 shows that Tobin's q increases for equity-constrained firms in response to favorable innovation shocks, while it decreases for debt-constrained firms. This rise in Tobin's q reflects an increase in the market valuation of the firm, which supports higher levels of investment. The increase in Tobin's q for equity-constrained firms is particularly pronounced during recessions, indicating that the relaxation of financial constraints may be more significant during economic downturns.

The market's positive valuation response to innovation shocks is further supported by changes in other financial metrics, including the growth rate of book value, liquidity, net equity, and net leverage. These responses are shown in Figure A.11 in the Appendix.[32] The increases in book value, liquidity, and net equity suggest a better financial position,

[31]Definitions of all financial variables, along with the Compustat variables used for their calculation, are provided in Table A.1.

[32]Several studies examine the cyclicality of firm financing, particularly regarding debt and equity financing, such as Covas and Den Haan (2011), Begenau and Salomao (2019), and Jermann and Quadrini (2012), though their analyses do not specifically address the impact of innovation shocks.

while the decrease in net leverage indicates that firms rely less on debt financing.

In summary, our findings suggest that equity-constrained, R&D-intensive firms exhibit the strongest responses to innovation shocks. Following positive innovation shocks, these firms experience increases in their market valuations, which they then use as a channel to ease their equity constraints and finance new investment. This mechanism becomes particularly important during recessionary periods, when external financing constraints are typically more binding.

5 Conclusion

This paper investigates how innovation shocks propagate through the economy, providing extensive empirical evidence using aggregate and firm-level data that recessions create growth opportunities for firms to fully benefit from innovations. To identify aggregate innovation shocks, we adopt a novel approach proposed by Cascaldi-Garcia and Vukotić (2022) who use firm-level stock market valuation changes triggered by news about patent grants.

Our findings suggest that the timing of the news matters. In response to an aggregate patent-based innovation shock, the economy exhibits a stronger response during recessions than in normal times, primarily driven by private investment. Motivated by this evidence, we investigate further by analyzing firm-level data. Using rich micro data on publicly listed U.S. firms, we show that following a favorable innovation shock, firms with low default risk invest significantly more than those with high default risk, with this gap widening in downturns. This result suggests that financial health plays a crucial role in determining which firms capitalize on innovation.

Financial constraints further shape firm responses, with debt constraints emerging as particularly important. While low-default-risk firms largely drive the overall investment response, we find that among firms facing financing frictions, investment is more restricted among the debt-constrained ones—those more exposed to default risk. In contrast, equity-constrained firms still exhibit a significant response to innovation shocks, highlighting that financial frictions do not uniformly suppress investment.

Our results reinforce the idea that recessions can present favorable conditions for growth-enhancing investment in response to innovation shocks. However, they also underscore the importance of financial frictions in shaping this process, as firms with greater financial flexibility remain best positioned to capitalize on new innovations.

References

Aghion, P., Askenazy, P., Berman, N., Cette, G., and Eymard, L. (2012). Credit Constraints and the Cyclicality of R&D Investment: Evidence From France. *Journal of* *the European Economic Association*, *10*(5), 1001–1024.

Aghion, P., and Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, *60*(2), 323–351.

Akcigit, U., and Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy*, *126*(4), 1374–1443.

Anzoategui, D., Comin, D., Gertler, M., and Martinez, J. (2019). Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence. *American Economic Journal: Macroeconomics*, *11*(3), 67–110.

Ates, S. T., and Saffie, F. E. (2021). Fewer but better: Sudden stops, firm entry, and financial selection. *American Economic Journal: Macroeconomics*, *13*(3), 304–356.

Atkeson, A., and Burstein, A. (2019). Aggregate implications of innovation policy. *Journal of Political Economy*, *127*(6), 2625–2683.

Auerbach, A. J., and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, *4*(2), 1–27.

Barlevy, G. (2007). On the cyclicality of research and development. *American Economic Review*, *97*(4), 1131–1164.

Barsky, R. B., and Sims, E. R. (2011). News shocks and business cycles. *Journal of Monetary Economics*, *58(3)*, 273–289.

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

Begenau, J., and Salomao, J. (2019). Firm Financing over the Business Cycle. *The Review of Financial Studies*, *32*(4), 1235–1274.

Bianchi, F., Kung, H., and Morales, G. (2019). Growth, slowdowns, and recoveries. *Journal of Monetary Economics*, *101*(C), 47–63.

Bloom, N., Jones, C. I., Van Reenen, J., and Webb, M. (2020). Are ideas getting harder to find? *American Economic Review*, *110*(4), 1104–1144.

Caballero, R. J., and Hammour, M. L. (1994). The Cleansing Effect of Recessions. *American Economic Review*, *84*(5), 1350–1368.

Caballero, R. J., and Hammour, M. L. (1996). On the timing and efficiency of creative destruction. *The Quarterly Journal of Economics*, *111*(3), 805–852.

Cascaldi-Garcia, D. (2024). Forecast revisions as instruments for news shocks. *Journal of Monetary Economics*, (p. 103729).

Cascaldi-Garcia, D., and Galvão, A. B. (2021). News and uncertainty shocks. *Journal of Money, Credit and Banking*, *53*(4), 779–811.

Cascaldi-Garcia, D., and Vukotić, M. (2022). Patent-based news shocks. *Review of Economics and Statistics*, *104*(1), 51–66.

Cloyne, J., Ferreira, C., Froemel, M., and Surico, P. (2023). Monetary Policy, Corporate Finance, and Investment. *Journal of the European Economic Association*, *21*(6), 2586–2634.

Comin, D., and Gertler, M. (2006). Medium-term business cycles. *American Economic Review*, *96*(3), 523–551.

Covas, F., and Den Haan, W. J. (2011). The cyclical behavior of debt and equity finance. *American Economic Review*, *101*(2), 877–99.

Crouzet, N., and Mehrotra, N. R. (2020). Small and Large Firms over the Business Cycle. *American Economic Review*, *110*(11), 3549–3601.

Crouzet, N., and Oh, H. (2016). What do inventories tell us about news-driven business cycles? *Journal of Monetary Economics*, *79*, 49–66.

Döttling, R., and Ratnovski, L. (2023). Monetary policy and intangible investment. *Journal of Monetary Economics*, *134*, 53–72.

Farre-Mensa, J., and Ljungqvist, A. (2016). Do Measures of Financial Constraints Measure Financial Constraints? *Review of Financial Studies*, *29*(2), 271–308.

Fernald, J. G. (2012). A quarterly, utilization-adjusted series on total factor productivity. Tech. Rep. 2012-19, Federal Reserve Bank of San Francisco.

Forni, M., Gambetti, L., and Sala, L. (2014). No news in business cycles. *Economic Journal*, *124*(581), 1168–1191.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In *New developments in productivity analysis*, (pp. 303–372). University of Chicago Press.

Francois, P., and Lloyd-Ellis, H. (2003). Animal spirits through creative destruction. *American Economic Review*, *93*(3), 530–550.

Gertler, M., and Gilchrist, S. (1994). Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms. *The Quarterly Journal of Economics*, *109*(2), 309–340.

Gilchrist, S., and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, *102*(4), 1692–1720.

Görtz, C., Gunn, C., and Lubik, T. A. (2022a). Is there news in inventories? *Journal of Monetary Economics*, *126*, 87–104.

Görtz, C., Tsoukalas, J. D., and Zanetti, F. (2022b). News shocks under financial frictions. *American Economic Journal: Macroeconomics*, *14*(4), 210–43.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence*, (pp. 287–343). University of Chicago Press.

Hoberg, G., and Maksimovic, V. (2014). Redefining Financial Constraints: A Text-Based Analysis. *The Review of Financial Studies*, *28*(5), 1312–1352.

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

Jeenas, P. (2019). Firm balance sheet liquidity, monetary policy shocks, and investment dynamics. Tech. rep., Working Paper.

Jermann, U., and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, *102*(1), 238–71.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665–712.

Kurmann, A., and Sims, E. (2021). Revisions in utilization-adjusted TFP and robust identification of news shocks. *Review of Economics and Statistics*, *103*(2), 216–235.

León-Ledesma, M., and Shibayama, K. (2023). (Endogenous) Growth Slowdowns. Tech. Rep. 18506, C.E.P.R. Discussion Papers.

Linn, M., and Weagley, D. (2023). Uncovering financial constraints. *Journal of Financial and Quantitative Analysis*, (p. 1–36).

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Miranda-Agrippino, S., Hoke, S. H., and Bluwstein, K. (2020). When creativity strikes: News shocks and business cycle fluctuations. *Centre for Macroeconomics (CFM) Discussion Papers*, *1823*.

Newey, W. K., and West, K. D. (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708.

Ottonello, P., and Winberry, T. (2020). Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica*, *88*(6), 2473–2502.

Ramey, V. A., and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from US historical data. *Journal of Political Economy*, *126*(2), 850–901.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5, Part 2), S71–S102.

Schaefer, S. M., and Strebulaev, I. A. (2008). Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds. *Journal of Financial Economics*, *90*(1), 1–19.

Schmitt-Grohe, S., and Uribe, M. (2012). What's news in business cycles. *Econometrica*, *80(6)*, 2733–2764.

Schumpeter, J. A. (1942). *Capitalism, socialism, and democracy*. New York: Harper and Brothers, New York (Routledge edition, 1994).

Segal, G., Shaliastovich, I., and Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, *117*, 369–397.

Shleifer, A. (1986). Implementation cycles. *Journal of Political Economy*, *94*(6), 1163–1190. Reprinted in N. Gregory Mankiw and David Romer, eds., New Keynesian Economics. Cambridge: MIT Press, 1991.

Sims, E. (2016). What's news in News? A cautionary note on using a variance decomposition to assess the quantitative importance of news shocks. *Journal of Economic Dynamics and Control*, *73*(C), 41–60.

Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, *39*(3), 312–320.

Stachurski, J., and Zhang, J. (2021). Dynamic programming with state-dependent discounting. *Journal of Economic Theory*, *192*, 105190.

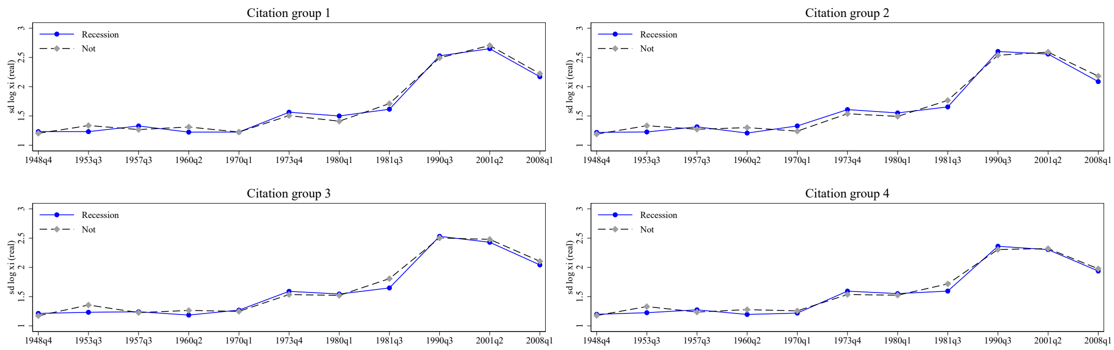
Tenreyro, S., and Thwaites, G. (2016). Pushing on a string: US monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, *8*(4), 43–74.

Vukotić, M. (2019). Sectoral effects of news shocks. *Oxford Bulletin of Economics and Statistics*, *81*(2), 215–249.

A Appendix

A.1 Cyclicality of Innovation Measures

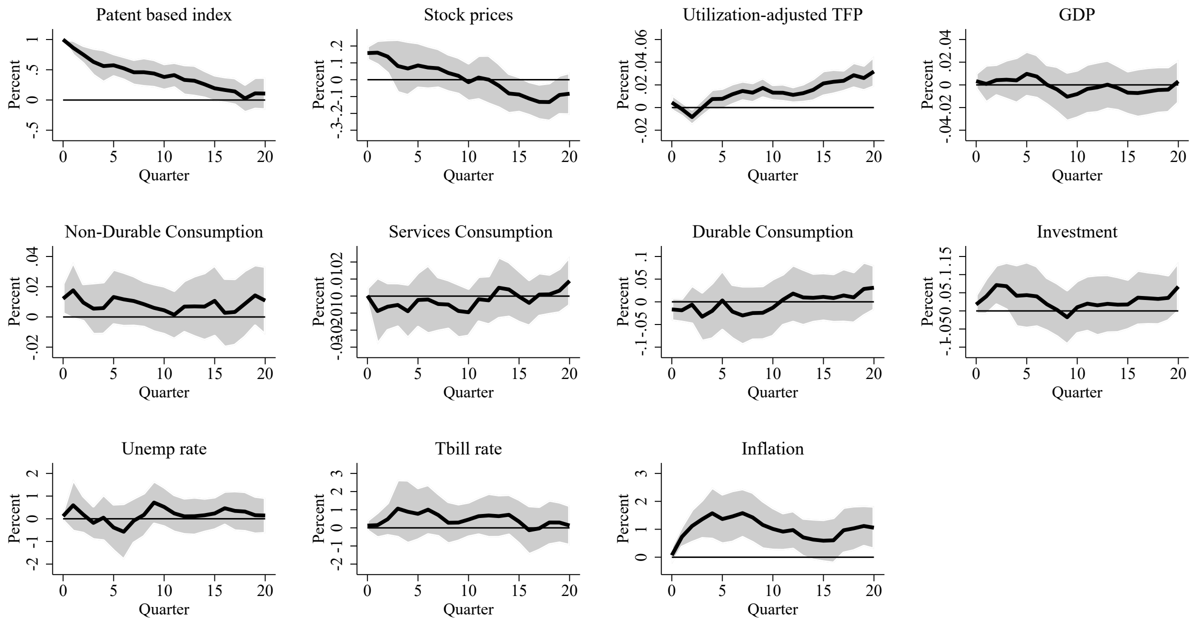
Figure A.1 Standard Deviation of real market valuation across states of the economy



Note: Each panel of the figure shows the standard deviation of real stock market valuation for a given recession (blue dots with solid lines) and the corresponding window of 8 quarters preceding and after it (gray dots with dashed lines), for a given citation group. The citation groups are divided into four quartiles of citations for a given recession.

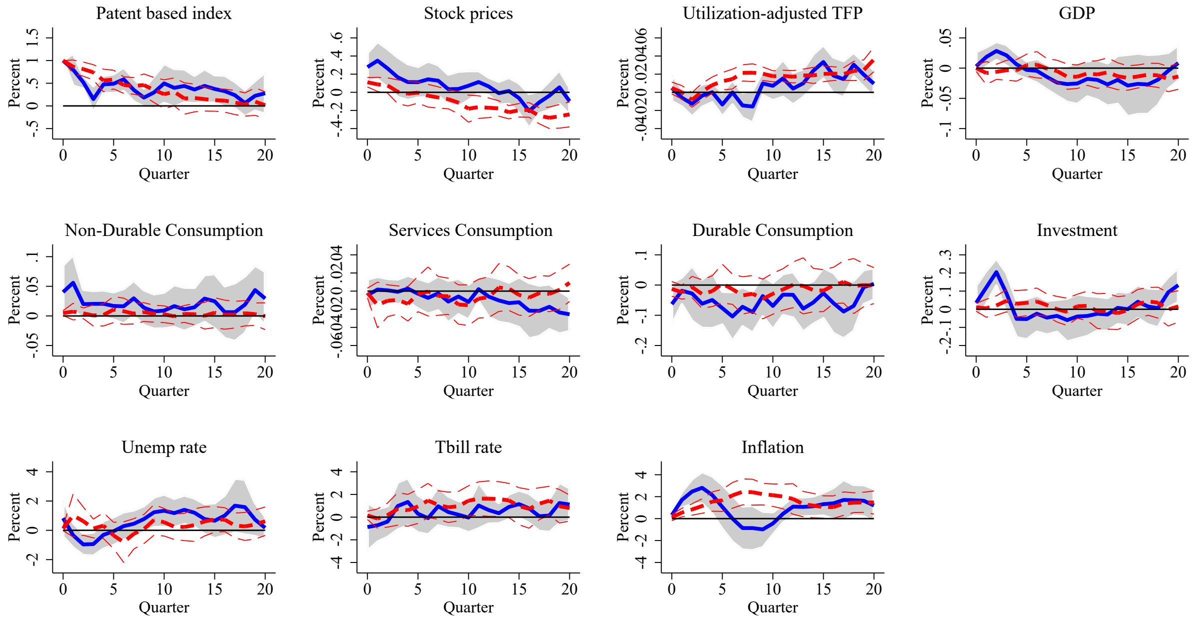
A.2 Aggregate Effects of Patent-Based Innovation Shocks

Figure A.2 Aggregate Analysis: Linear effects of patent-based innovation shocks - Additional Variables



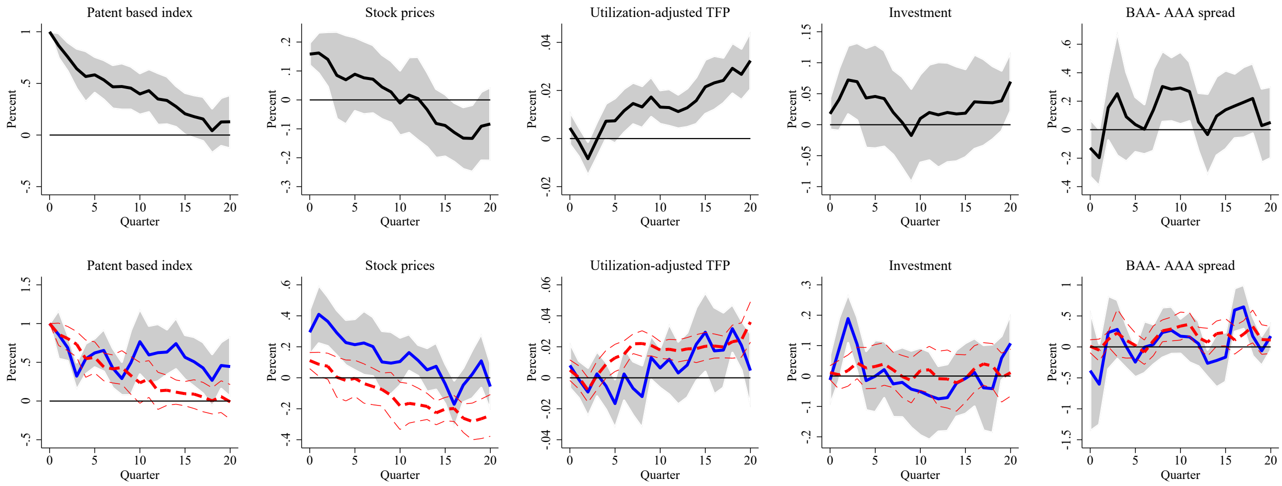
Note: Corresponding 90% confidence bands shown. Sample period: 1947-2019.

Figure A.3 Aggregate Analysis: State-dependent Effects of Patent-Based Innovation Shocks - Additional Variables



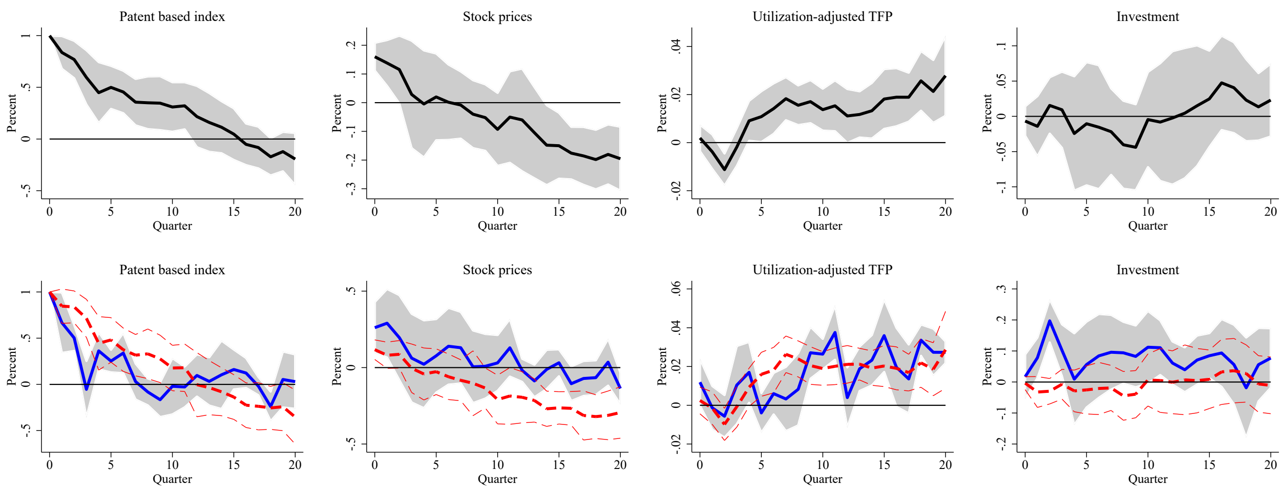
Note: in recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown. Sample period: 1947-2019.

Figure A.4 Aggregate Analysis: Effects of patent-based innovation shocks - Robustness to credit controls



Note: Corresponding 90% confidence bands shown. Sample period: 1947-2019. These are linear and state-dependent responses to the patent-based index where the lags of BAA-AAA credit spread are added as additional control. The last column shows the response of the BAA-AAA credit spread to the innovation shock.

Figure A.5 Aggregate Analysis: Effects of patent-based innovation shocks - Shorter sample

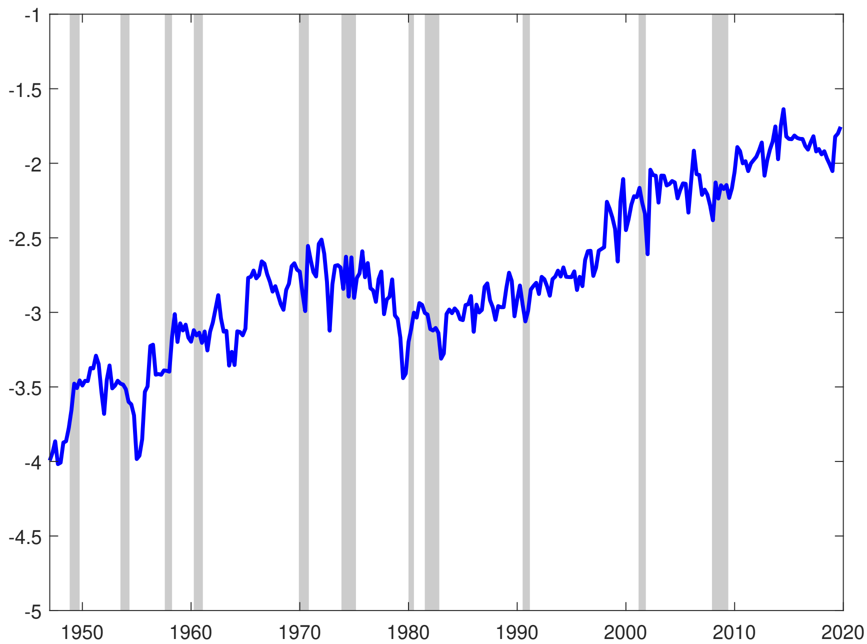


Note: The top row shows the linear responses and the bottom row shows the stat-dependent responses for recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown. Sample period: 1966-2019.

A.2.1 Alternative Use of Patents to Capture Innovation Shocks

Distinguishing between movements induced by news about future technological changes and the actual realization of these changes poses a challenge when using TFP data and standard news shocks identification methods based on forecast error variance decomposition, as highlighted by Sims (2016). The author refers to these two types of news as "pure news" and "realized news." Our approach, using patent data, likely captures "pure news"—the economic effects of expected technological changes—rather than the actual realization of those changes.

Figure A.6 PATENT CITATION-WEIGHTED QUARTERLY INNOVATION INDEX

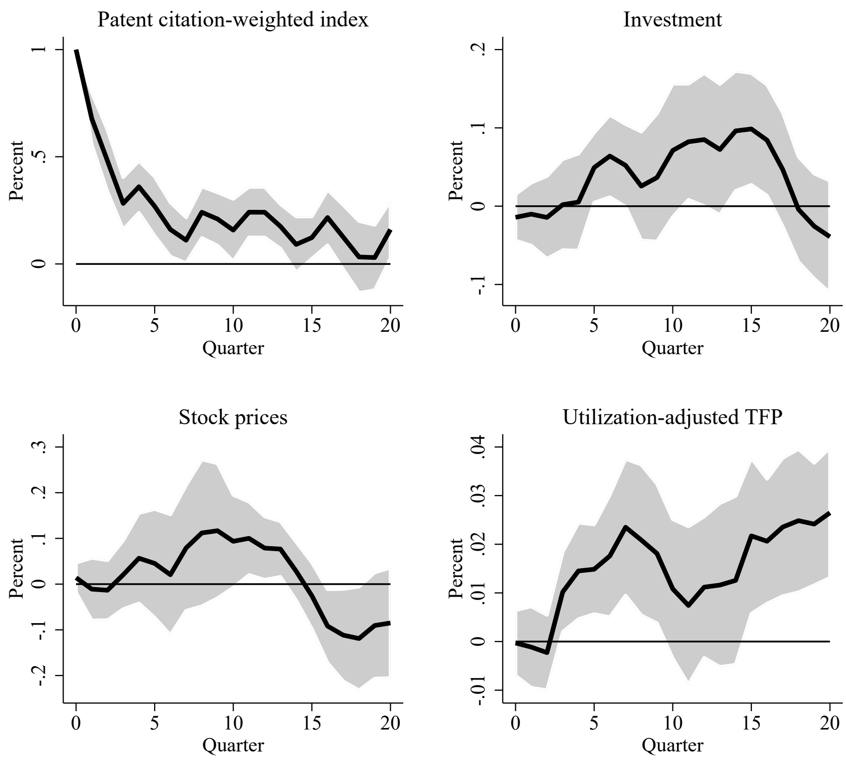


Note: Log of the aggregate quarterly per capita patent citation weighted innovation index constructed following the procedure described in Section 3.1, spanning 1947:Q1 - 2019:Q4. The shaded vertical bars represent the National Bureau of Economic Research (NBER) dated recessions.

We tease out movements due to realized news by considering an alternative measure of innovation: a citation-weighted patent count for a firm. In particular, we consider a metric that counts the number of forward citations of patents issued in a given quarter, and consider a shock to this index.[33] While market movements capture the immediate reaction of economic agents to the innovation, citations take time to accumulate due to

[33]This measure is constructed using the approach of Kogan et al. (2017), as follows. For a given quarter, t, we count the total number of citations C a patent j receives in the future, and construct: $\sum_{j\in t}\left(1+\frac{C_j}{\bar{C}_j}\right)$, where $\bar{C}_j$ is the average number of forward citations received by patents issued in the same quarter as patent j. This helps account for the fact that patents issued at the end of the sample have not had time to accumulate citations to reflect their scientific value.

Figure A.7 Aggregate effects of an alternative measure: patent citation-weighted index shocks



Note: The black solid lines are the impulse responses of the aggregate variables, which represent the estimates of β_h obtained from equation 2 when we consider the patent citation-weighted index instead of a patent-based innovation index. The shaded areas are 90% confidence bands.

rigorous peer-reviewed evaluations, disruptive potential, and and ultimate importance of the technology for future innovation. In sum, forward citations provide insight into the scientific value and significance of patents and represent the realization of technological advancements anticipated by the initial patent grant.[34]

Figure A.7 replicates our empirical exercise using the citation-weighted measure instead of the benchmark patent-based innovation index. The results support our interpretation that changes in the citation-weighted measure reflect realized news. Specifically, a positive shock to this measure leads to a delayed response in utilization-adjusted TFP, indicating that it captures future realized gains that materialize in TFP over time. In contrast, both stock prices, investment and (though not shown) GDP exhibit no immediate impact response. Investment rises with a delay when the TFP gains are realized. This

[34]Figure A.6 shows the log of the aggregate quarterly patent citation weighted index. It is positively correlated with the patent-based innovation index shown in Figure 1, with a correlation of close to 0.7. However, the two series do differ in some periods, particularly during the late 1990s when the market valuation based index suggests higher value of innovation than forward citation based measure and therefore dominance of pure news.

delayed response in investment and stock prices, following TFP developments, contrasts sharply with the anticipatory behavior seen in Figure 4. This suggests that citation-weighted measure captures realized technological advancements, while the patent-based innovation index reflects pure news.

A.3 Data Construction: Aggregate Variables

In the aggregate analysis, we use quarterly aggregate data that span the period from 1947:Q1 to 2019:Q4. The series that we use are the following:

- Patent-based innovation index constructed following Cascaldi-Garcia and Vukotić (2022).
- The output measure is the log of real output in the nonfarm business sector (BLS: PRS85006043). The series is recovered from the Bureau of Labor Statistics (BLS).
- The hours series is the log of the total hours worked in the same sector (BLS: PRS85006033). The series is recovered from the Bureau of Labor Statistics (BLS).
- The consumption measure is personal consumption expenditures on nondurables and services (Bureau of Economic Analysis (BEA) Table 1.1.3., sum of lines 5 and 6).
- The consumption durable measure is personal consumption expenditures on durables (Bureau of Economic Analysis (BEA) Table 1.1.3., line 4).
- The investment series is gross private domestic investment (BEA Table 1.1.3., line 7).
- The stock price measure is the log of the Standard and Poor's 500 Composite Stock Price Index, recovered from Robert Shiller's website.

We transform all these series into per capita values by dividing them by the BLS series of the civilian noninstitutional population over 16 (LNU00000000Q). We also calculate real values by adjusting for inflation using the GDP deflator.

- The TFP measure is the log of the utilization-adjusted measure provided by Fernald (2012).
- The inflation measure is the percentage change in the CPI for all urban consumers (CPIAUCSL, St. Louis FRED).
- The federal funds rate series is the effective federal funds rate from the Board of Governors (FEDFUNDS, St. Louis FRED).

A.4 Data Construction: Firm-level Variables

This section describes the firm-level data construction steps used in the main analysis of the paper.

A.4.1 Data Source

- The main data source in the paper is the quarterly North-America Compustat accessed through WRDS, which covers various firm-level characteristics.
- The firm-level patent information is from the data, constructed and provided by Kogan et al. (2017). It includes the economic value of the patent, citation, and also the date when the patent is applied/issued.
- For the firm specific patent and the analysis using the information, we rely on CRSP-Compustat merged dataset. This is because KPSS dataset reports firm identifier in the CRSP (permno), we need to merge the sample using the links between identifiers in Compustat (gvkey).

A.4.2 Sample Selection

- Our empirical analysis excludes firm-quarter observation with negative values of the following variables: Sales, Current and Total Asset, Property, Plant and Equipment - Total (Gross) and (Net), Research and Development Expense, Selling, General and Administrative Expenses, Inventories, Dividends, Capital Expenditures
- We also trim outliers by excluding observations of the following variables, if they are in the top or bottom 1% of the distribution: Inventories to Sales Ratio, R&D to Sales Ratio, Leverage, Net Leverage, Short-term Investment to Debt Ratio, Liquidity, Liquidity Ratio, Investment Ratio, Distance to Default.
- We also exclude firms in the sectors: finance, insurance, and real estate, utilities, non-operating establishments, and industrial conglomerates.
- We only consider domestic firms incorporated in the United States where their balance sheet is reported in the US dollars.

A.4.3 Variable Description

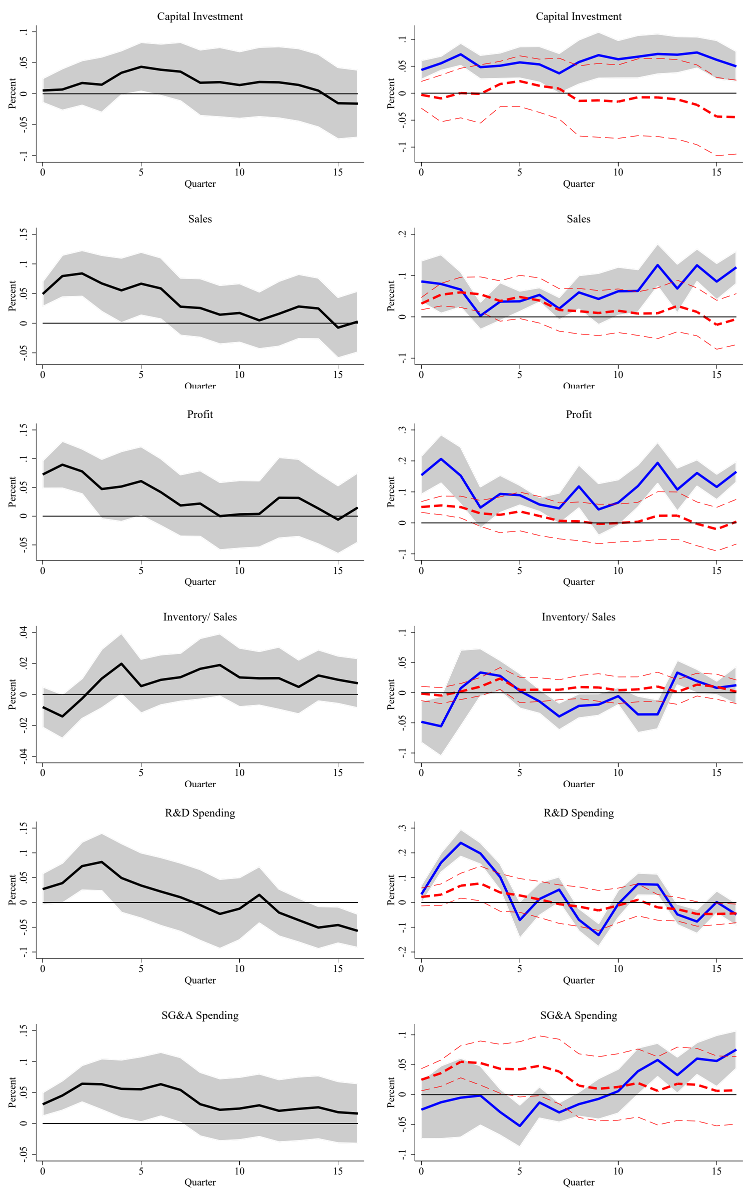
The exact definition of variables is shown in Table A1, where we tend to closely follow Ottonello and Winberry (2020) and Kogan et al. (2017).

Table A.1 Firm-Level Variable Definitions

Variable	Compustat Variable	Variable Description
Capital Stock	ppegtq, ppentq	Property, Plant and Equipment - Total (Gross) and (Net)
Sales	saleq	Sales/Turnover (Net)
R&D	xrdq	Research and Development Expense
Inventory	invtq	Inventories - Total
Output	saleq + d.invtq	Total sales plus changes in inventory (KPSS)
Profit	saleq - cogsq	Sales minus Cost of Goods Sold
R&D to Sales Ratio	xrdq/saleq	
SG&A to Sales Ratio	xsgaq/saleq	xsgaq: Selling, General and Administrative Expenses
Inventories to Sales Ratio	invtq/saleq	
Leverage	(dlcq+dlttq)/atq	Ratio of Total Debt to Total Asset
Net Leverage	(lctq +dlttq -actq)/atq	Ratio of Total Debt minus Net Current Asset to Total Asset
Firm Size	atq	Total Assets
Liquidity	cheq/atq	Cash and Short-Term Investments over Total Asset
Book value	cshoq*prccq	Outstanding shares multiplied by the closing price
Tobin's q	(atq + cshoq*prccq - ceqq + txditcq)/atq	ceqq: Common/Ordinary Equity txditcq: Deferred taxes and investment tax credit
Net Equity	(sstky-prstkcy)/atq(-1)	Sale of common and preferred stock minus purchase of common and preferred stock scaled by lagged total assets

A.5 Firm-Level Effects of Patent-Based Innovation Shocks

Figure A.8 Average firm-level effects of patent-based innovation shocks (left) and state-dependent (right) - Without additional controls



Note: Left panels present linear results and right panels present state-dependent results, with recessions in blue and normal times in red. Corresponding 90% confidence bands shown.

Table A.2 Firm-Level Characteristics Correlation Matrix

	Leverage	Liquidity	Size	Dist. to Default	Net Leverage	GG Size
Leverage	1.000					
Liquidity	-0.224	1.000				
Size	0.106	-0.174	1.000			
Dist. to Default	-0.354	0.113	0.346	1.000		
Net Leverage	0.797	-0.447	0.228	-0.256	1.000	
GG Size	0.062	-0.327	0.592	0.194	0.121	1.000

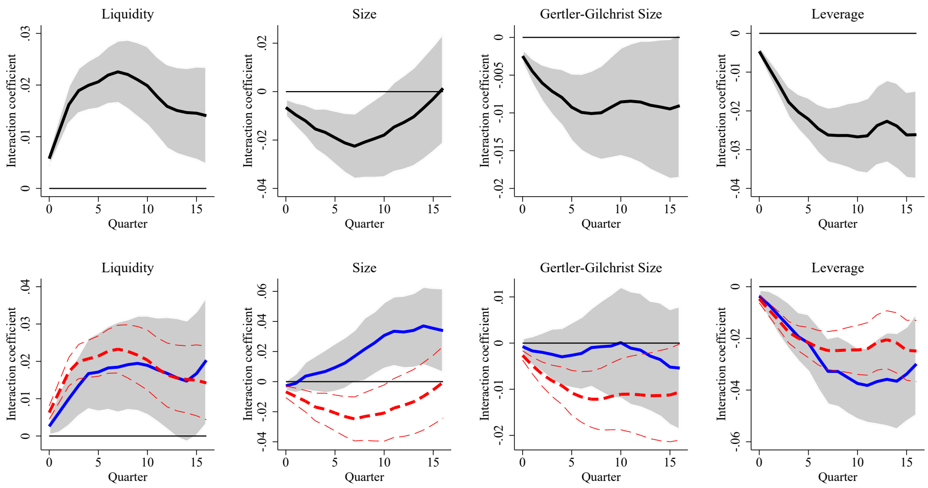
Note: This table shows the correlation matrix of the firm characteristics from 1985q1-2019q4. Leverage is ratio of total debt to total assets. Liquidity is the ratio of cash and short term investments to total assets. Size is given by total assets of the firm. Net leverage is the ratio of total debt minus net current assets to total assets. The GG size measure is based on Gertler and Gilchrist (1994) and identifies a small firm if its average sales over the past 10 years is below the 30th percentile of the distribution.

Table A.3 Firm-Level Characteristics Correlation Matrix

	Leverage	Liquidity	Size	Net Leverage	GG Size	Equity constraint	Debt constraint	R&D intensity
Leverage	1.000							
Liquidity(S)	-0.245	1.000						
Size (Asset)	-0.069	-0.182	1.000					
Leverage(N)	0.795	-0.380	-0.083	1.000				
Gertler-Gilchrist size	-0.054	-0.313	0.666	-0.027	1.000			
Equity constraint	0.030	0.465	-0.318	-0.002	-0.478	1.000		
Debt constraint	0.206	-0.515	0.273	0.189	0.349	-0.374	1.000	
R & D intensity	0.007	0.302	-0.131	-0.022	-0.246	0.330	-0.145	1.000

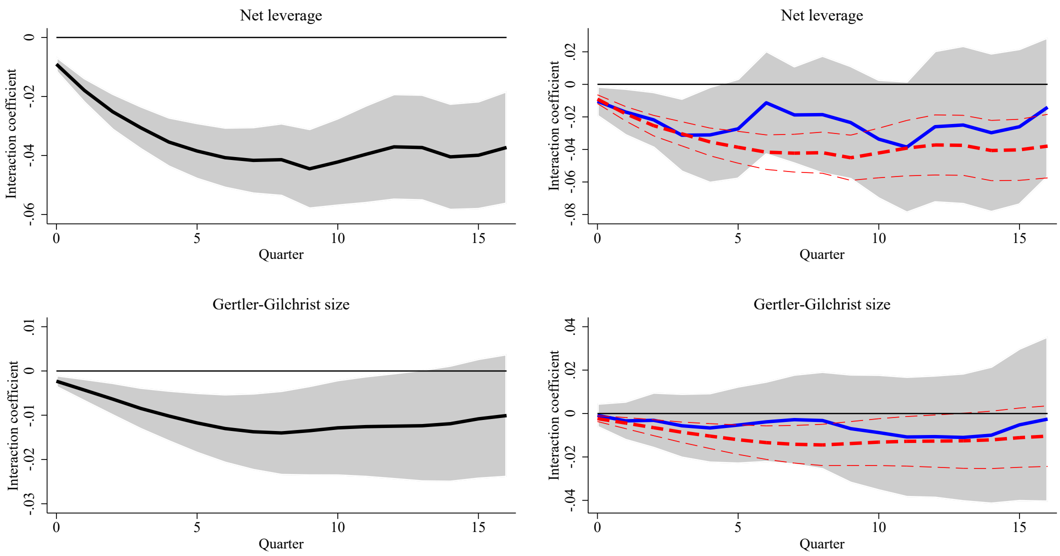
Note: This table shows the correlation matrix of the firm characteristics from 1972q1-2019q4. Leverage is ratio of total debt to total assets. Liquidity is the ratio of cash and short term investments to total assets. Size is given by total assets of the firm. Net leverage is the ratio of total debt minus net current assets to total assets. The GG size measure is based on Gertler and Gilchrist (1994) and identifies a small firm if its average sales over the past 10 years is below the 30th percentile of the distribution. Equity-based constraint and debt-based constraint are from Linn and Weagley (2023). R& D intensity is given by R&D to sales ratio. Note adding the R&D intensity variable reduced the sample under consideration for that particular correlation, cross-sectionally, given its relatively limited data availability.

Figure A.9 Average and state-dependent capital investment response based on the firm characteristics



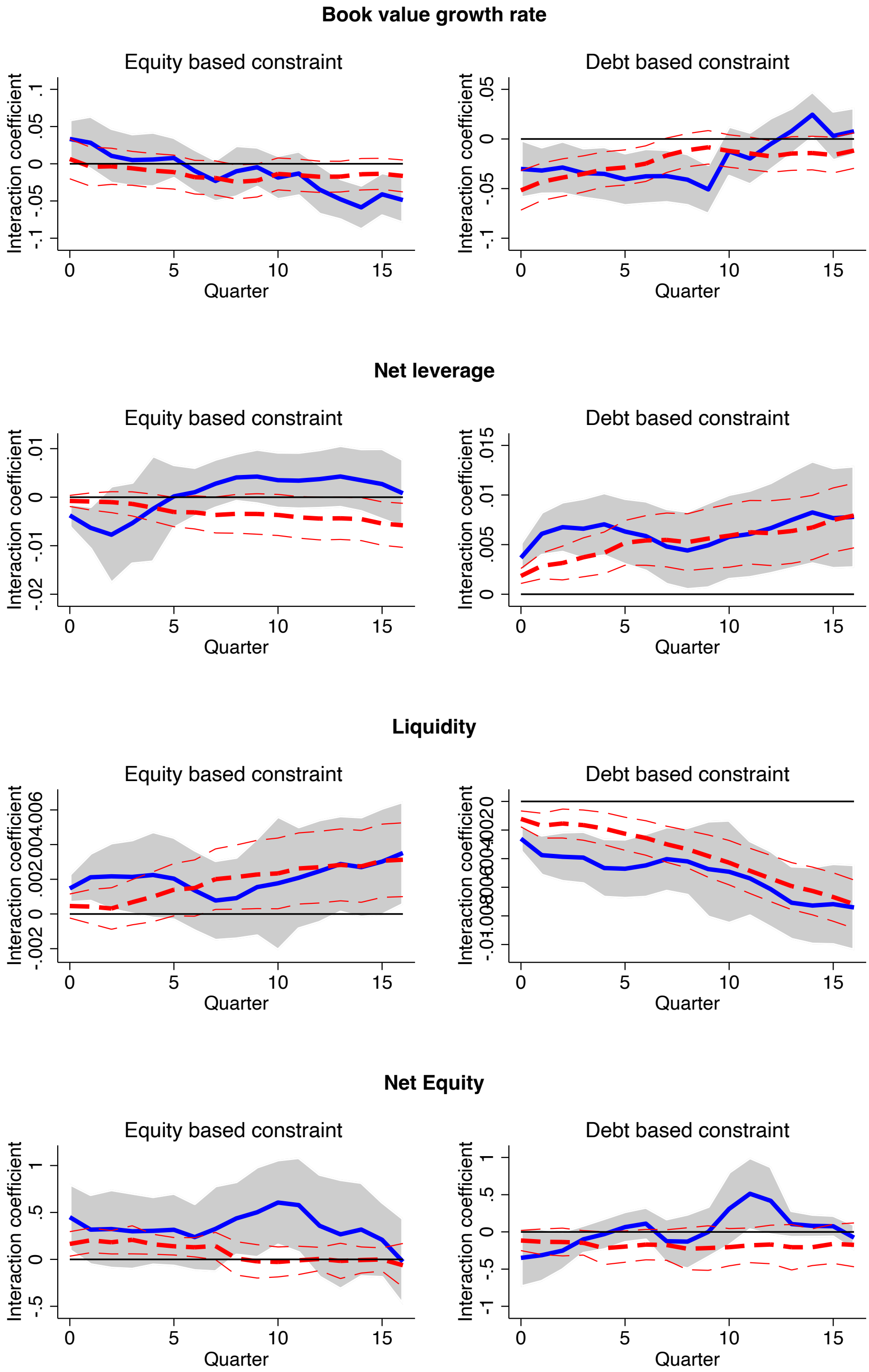
Note: Average (top row) and state-dependent (bottom row) dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks. In recessions (blue solid) and normal times (red dashed), for sample period spanning 1966-2019. Corresponding 90% confidence bands shown.

Figure A.10 Capital investment response based on additional firm characteristics



Note: The left panels show the average dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks. The right panels show the state-dependent dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks, in recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown, for sample period 1984-2019.

Figure A.11 State-dependent responses of various financial variables based on the firm characteristics



Note: Dynamics of the coefficient of the firm characteristic interacted with patent-based innovation shocks, both linear (top panel) and non-linear (bottom panel). Recessions are indicated by solid blue lines, and normal times by dashed red lines. Corresponding 90% confidence bands shown.