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Innovation During Challenging Times*

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Abstract

When is receiving positive news regarding future technological advancements most impactful on the economy: during recessions or economic booms? A recession might represent an opportune time for investing in relatively cheaper, productivity-enhancing activities. However, tighter financial constraints during recessions might hinder the ability to secure funds for these activities. We explore this dichotomy by exploiting patent-based innovation shocks, which are constructed using changes in stock market valuations of firms that obtain patent grants. We find that aggregate patent-based innovation shocks have a greater impact on the economy during recessions, leading to a more significant increase in private investment. Additionally, our exploration of firm-level data uncovers supporting evidence that firms tend to boost their capital investment and R&D expenditures in response to these innovation shocks, particularly during recessions. The financial constraints of firms play a crucial role, with capital investments by firms with low default risk driving the larger impact observed during recessions.

Keywords: Innovation shocks, Patent-Based Innovation Index, Financial Frictions, Firms heterogeneity, State dependency

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1 Introduction and Motivation

As the extensive endogenous growth literature has documented, economic growth is only possible with continuous technological advancements and innovation (Solow, 1957, Romer, 1990, Aghion and Howitt, 1992). We approach this broad and essential topic from the lens of business cycles by analyzing how the economy responds to innovation advancements and whether the response differs depending on the prevailing economic conditions.

On the one hand, since Schumpeter (1942), many economists have argued that recessions are ideal times for conducting productivity-enhancing activities. This argument is based on the premise that these activities are more cost-effective during economic downturns when the opportunity cost of forgone output and sales is low. As a result, firms may be more receptive to favorable innovation shocks during recessions. On the other hand, firms are more likely to encounter financial constraints during economic downturns, potentially making it difficult for them to secure the required investments to fully realize the benefits of innovation. Also, firms may prioritize short-term profits and delay implementing new technologies until demand conditions improve.

This paper investigates which of the two forces is dominant by empirically examining how the economy reacts to aggregate innovation shocks triggered by good news about patent grants. Our findings indicate that the timing of these positive patent-grant related news matters. Specifically, when facing an aggregate patent-based innovation shock, the economy exhibits a stronger response during recessions compared to expansions, with private investment playing a key role. This stronger response persists when analyzing firm-level data, where we provide evidence that recessions indeed stimulate investment and innovative activities at the firm level in response to news about patent grants.

We identify innovation shocks using stock market reactions to news about patent grants, following the approach proposed by Cascaldi-Garcia and Vukotić (2022). When a patent is granted, information about the future potential of the new process or product that is being patented is revealed, which in turn triggers a reaction in the stock market. Because most patented technologies require additional time and resources to become operational, the immediate market reaction that follows the grant of a patent essentially represents the market valuation of that innovation's future technological and economic potential. Therefore, capturing changes in these valuations allows us to capture shocks related to the future technological potential of granted innovation ideas.

Our aggregate analysis reveals that an identically sized increase in the patent-based innovation index results in a positive and significant response of private investment during recessions, while showing an insignificant response during expansions. Moreover, stock prices exhibit a rise in response to an innovation shock immediately after its occurrence, which is not statistically significantly different across the two states. Utilization-adjusted total factor productivity (TFP), which is traditionally used as a proxy for technological progress, shows an insignificant response on impact in both states of the economy, but rises to similar levels at longer horizons. In summary, our aggregate findings suggest that patent-based innovation shocks have different propagation patterns in recessions and expansions, with a larger impact on aggregate private investment observed during economic downturns.

Motivated by this aggregate evidence, we further investigate the propagation of patent-based innovation shocks at a disaggregated level. While the propagation of technological news and innovation shocks has been studied at the aggregate level within the literature, one of the contributions of this paper is to delve into its transmission mechanism and consider how firms respond to aggregate innovation shocks, and whether the state of the economy plays a role in their response. Examining the average reaction of firms is crucial because they are catalysts of innovation and growth.[1]

Notably, we investigate which firms are most responsive to innovation shocks using comprehensive firm-level data. We rely on the Compustat database, a panel that provides detailed balance-sheet and income-statement information about all publicly traded U.S. firms. Despite publicly listed companies accounting for about 60 percent of total investment in the U.S., the dynamics of the capital expenditures series constructed from the firm-level data is highly comparable to the dynamics of the aggregate investment series provided by the U.S. Bureau of Economic Analysis. Therefore, we consider our analysis as a step towards understanding the aggregate effects of these innovation shocks for aggregate investment by considering how much can be explained by the dynamics of publicly traded firms.

We find that firms with healthier financial positions, as measured by high liquidity, low leverage, and higher distance to default, exhibit larger responses of capital investment to innovation shocks, potentially due to their enhanced access to funding and resources for capitalizing on new technological opportunities. Moreover, we observe that the effects of innovation shocks on firm investment, R&D expenditures, and other related variables are even more pronounced during economic recessions. These findings align with the Schumpeterian view that it may be cheaper for firms to engage in innovative activities during recessions. We provide further evidence that the heightened impact of innovation shocks on firms with stronger financial conditions or low credit risk is further amplified during periods of economic downturn, underscoring the pivotal role of financial health in shaping firms' response to aggregate innovation shocks.

Related Literature. Our study contributes to multiple strands of the literature on innovation and firm dynamics over the business cycle. First, our paper provides valuable

[1]Note that 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-wide response to the arrival of news about future innovations, which capture diffusion of ideas and general equilibrium effects.

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 because it relies 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 patent-based innovation shocks using rich firm-level data.[3]

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 TFP and knowledge accumulation stemming from R&D spending (See for example, Barlevy, 2007, Comin and Gertler, 2006, Anzoategui, Comin, Gertler, and Martinez, 2019, and Bianchi, Kung, and Morales, 2019). 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 countercyclical conditional on innovation shocks, which is in line with the result of Aghion, Berman, Eymard, Askenazy, and Cette (2012) who analyses the R&D investment on 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 and find 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 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 (2019), 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) investigate how different types

[2]The literature on technological news shocks is extensive. See, among others, Beaudry and Portier (2006), Jaimovich and Rebelo (2009), Barsky and Sims (2011), Schmitt-Grohe and Uribe (2012), Kurmann and Otrok (2013), Kurmann and Mertens (2014), Forni, Gambetti, and Sala (2014), Crouzet and Oh (2016), Görtz and Tsoukalas (2017), Cascaldi-Garcia (2017), Miranda-Agrippino, Hoke, and Bluwstein (2020), Görtz, Tsoukalas, and Zanetti (2020), Kurmann and Sims (2021), and Cascaldi-Garcia and Galvão (2021).

[3]Previous studies, such as Cascaldi-Garcia (2019) and Forni, Gambetti, and Sala (2023), explored the link between the technological news shocks and the level of uncertainty in the economy

of investment react to monetary policy shocks and find that the investment and stock prices 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 encompassing linear and state-dependent effects of innovation shocks at the aggregate and the firm level, respectively. Section 5 concludes.

2 Patent-Based Innovation Shock

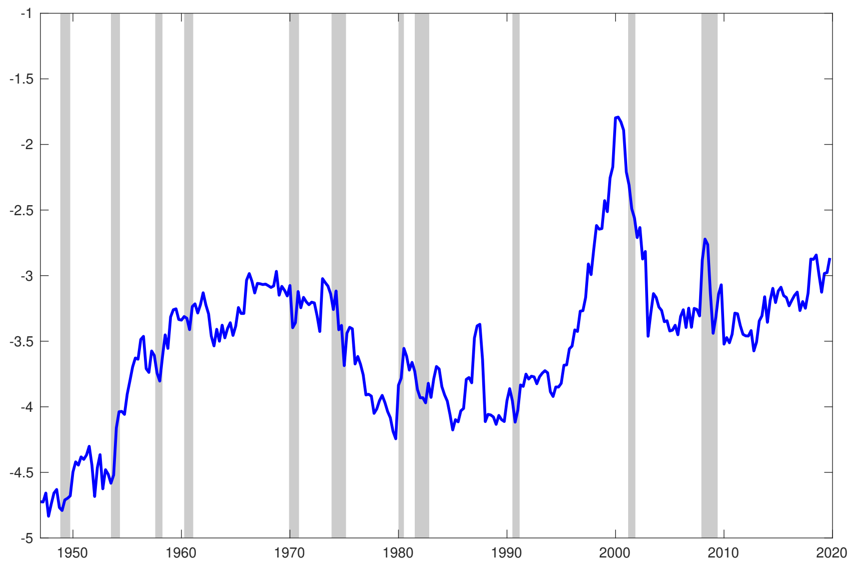
We use the quarterly patent-based innovation index constructed by Cascaldi-Garcia and Vukotić (2022) to measure the market valuation of future technological potentials. Figure 1 presents the evolution of the index for the post-World War II period, spanning from 1947:Q1 to 2019:Q4, which corresponds to the time period 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, which is then scaled by the aggregate output. This scaling by aggregate output is in line with an innovation model, as outlined in Atkeson and Burstein (2019), in which firms generate monopoly profits through innovation. These profits have a linear relationship with both aggregate output and TFP. To obtain the economic value of each patent we use the work of Kogan, Papanikolaou, Seru, and Stoffman (2017), who rigorously extract information about the economic value of each patent using high-frequency movements in stock prices triggered by a patent grant. This approach effectively filters out noise and unrelated news.[4]

The index effectively tracks periods of technological booms and slowdowns. For example, it increases during the substantial innovation surge in the 1960s and 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 it later stabilized.

We interpret exogenous variations in this index as the *patent-based innovation shocks* because its movements can be directly linked to actual patent granting activity and changes in firms' stock evaluations. These innovation shocks are reminiscent of and closely related to the original idea proposed by Beaudry and Portier (2006), which has spurred a broad and prominent literature about the effects of anticipated technology advancements on the economy. Our shock is connected to the original idea of technological news precisely because our identification relies solely on micro-level data on patenting activity and subsequent stock market reactions, capturing the present value of the expected current and future stream of revenues stemming from the innovation. However, given the focus on patenting activity by publicly listed firms, it is somewhat different

[4] 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 1947:Q1 - 2019:Q4. The shaded vertical bars represent the National Bureau of Economic Research (NBER) dated recessions.

from a technological news shock that attempts to identify all anticipated information about future TFP movements.

Given the extensive discussion on the benefits of this approach, including the avoidance of structural restrictions and the utilization of an empirical measure of TFP for identification, as highlighted in Cascaldi-Garcia and Vukotić (2022), we refrain from delving into the comparison of our shocks with other approaches in the literature. Instead, we provide a brief justification for considering 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, with the patent grant conveying specific information about the future potential of that innovation. One way to quantify this potential is to measure stock market reactions to the information revealed with the grant.[5] Most patented technologies require additional time and resources to become operational, and the immediate market reaction that follows the grant of a patent essentially reflects the market's valuation of

[5]The response of market participants to this information, as uncovered by Kogan et al. (2017), completes our story. Merely counting the number of patents would not be sufficient for uncovering the future innovation potential, as the number itself masks the differences in nature and expected outcomes of patents, which can have varying effects on firm-level and aggregate productivity. For example, comparing the potential aggregate effect on the economy of a patent from a pharmaceutical company with that of a patent from an electronics company would be challenging.

the future technological and economic potential of that patented innovation. Therefore, capturing changes in these valuations amount to capturing shocks about the future technological potential of granted innovation ideas, which is why we refer to these changes as patent-based innovation shocks.

3 Innovation Shocks and Aggregate Dynamics

In order to understand the effects of innovation activity on the economy, we undertake a comprehensive analysis encompassing linear and state-dependent effects of innovation shocks both at the aggregate and at the firm level. We start things off in this section by conducting an initial linear analysis in a longer sample dating back to the aftermath of the second World War, mostly corroborating the findings of Cascaldi-Garcia and Vukotić (2022).

Subsequently, we justify the importance of the non-linear analysis and evaluate the state-dependent aggregate effects of innovation shocks. As discussed in detail throughout the section, we venture the possibility that the effects of innovative activity may vary depending on the state of the economy. We base this assertion on the fact that, although a technological innovation takes time to be implemented, economic agents react to its expected future potential at the time the innovation is publicly disclosed, as well as on empirical evidence linking the effects of technological shocks and the state of the economy.

Lastly, we highlight the relevance of examining firm-level data to uncover specific firm characteristics that play a key role in the transmission of innovation shocks within the economy, also focusing on potential state-dependencies.

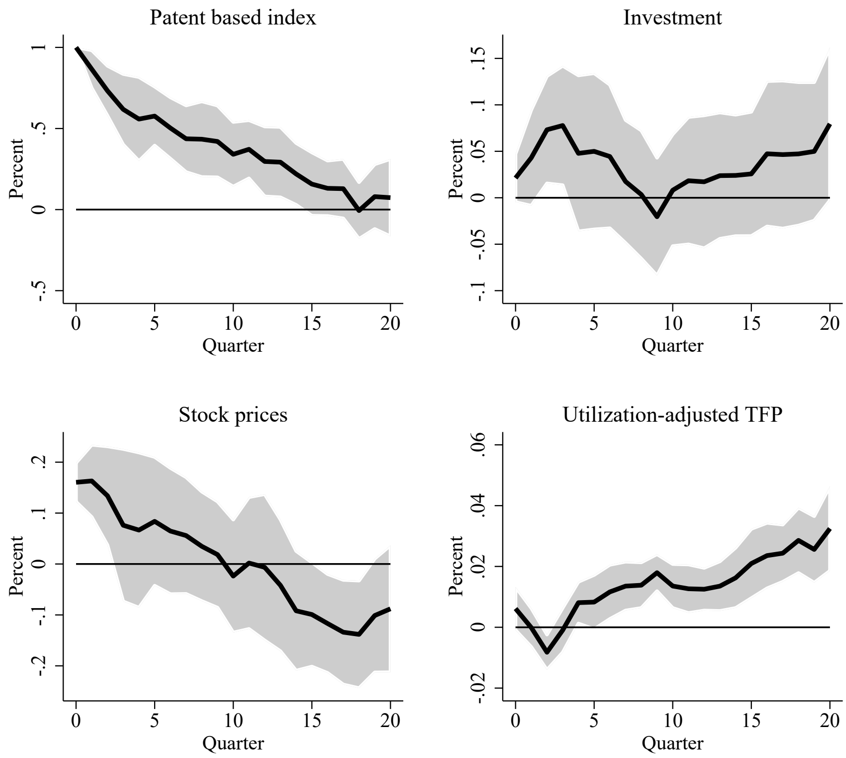
3.1 Aggregate Effects of Patent-Based Innovation Shocks

In order to evaluate the linear effects of a patent-based innovation shock to our variables of interest, we run local projections (as in Jordà, 2005) with the following specification,

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

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. This vector includes 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.2. The coefficient β_h on the innovation index gives the response of the variable z_t to an innovation shock at horizon h. Therefore, the local projections allow us to trace the impulse response of the variable of interest to the patent-based innovation shock. Given the serial correlation induced by the Jordà method, we use the Newey-West correction for our standard errors (Newey and West, 1987). Our quarterly data spans the post World-War II period, from 1947:Q1 to 2019:Q4.

Figure 2 AGGREGATE ANALYSIS: LINEAR EFFECTS OF PATENT-BASED INNOVATION SHOCKS



Note: The black solid lines are the impulse responses of the aggregate variables, which represent the estimates of β_h obtained from equation 1. The aggregate control variables include two lags of the patent-based innovation index, real GDP, unemployment rate, T-bill rate, inflation, aggregate S&P500 index and utilization-adjusted TFP. The shaded areas are 90% confidence bands.

Figure 2 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 increases on impact, with a peak effect about one year after the innovation shock exhibiting a hump-shaped reaction, similar to in response to other macroeconomic shocks. Stock prices react instantaneously, with positive and significant effects for about three quarters after the shock. Interestingly, utilization-adjusted TFP, a proxy for the technological level of the economy, does not respond immediately but rather with a delay. The first positive and significant effect is observed about five quarters after the innovation shock.

Two main results stem from these responses. First, the long delay between the shock to patent grants and the actual effect on productivity suggests that the innovation shock encompasses the anticipated component of a future technological change. Second, the fact that investment reacts before any productivity increase has occurred indicates that firms are reacting and adapting their plants to the *expected* increase rather than tracking the 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.

3.2 Rationale for State Dependence

The *rationale* for studying state dependence stems from the very nature of innovation shocks. Technological innovations are often associated with adoption delays, which means that agents not only respond to the immediate economic outcomes of the innovation but also to the *expected* future stream of outcomes that the innovation is anticipated to bring.

Because the state of the economy can directly affect how agents react to innovation shocks and their expectations of future outcomes, it becomes even more critical when making decisions. For example, consider a firm that receives the news that a specific technology would increase its productivity with some delay (say, an automation development on the production line). From the firm's perspective, such technology has an expected positive return, but adaptations will be necessary to the production plant. A direct effect is that the firm will need to invest now (or ahead of the technology implementation) to take on board the innovation, and an indirect effect is that the firm may smooth future revenues over time by spending now. However, the firm's ability and willingness to do so depend markedly on economic conditions outside of its control, such as the state of the economy. From a theoretical perspective, it is reasonable to think that agents could have state-dependent discount factors about these future streams, and occasionally binding financial constraints would also play a role in the decision.[6]

Two opposing forces may affect the firms' investment decisions during recessions. On the one hand, financially constrained firms may find it arduous to fund their investment appetite, while this may not be the case in tranquil times. On the other hand, the willingness to invest may be higher during challenging times, as innovations also present an opportunity for growth (Segal, Shaliastovich, and Yaron, 2015); conditional on access to credit, the economic effect would be higher in recessions than in tranquil times. As an additional observation, from an aggregate perspective, economic agents observe the firms'

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

dichotomy, evaluate the data, make assumptions about the firms' decisions in each state of the economy, and react accordingly. As economic agents may also behave differently during recessions and tranquil times due to different factors—such as state-dependent risk aversion, discount factor, confidence, access and quality of information—, their attitude toward the firms' innovative activity adds an extra layer of potential state-dependency at the aggregate level. Which force dominates the aggregate response to innovation improvements is an empirical question that we uncover in the next part of the paper.

While largely unexplored by the literature, some empirical studies have hinted that technological changes may present different outcomes based on the state of the economy. For example, Cascaldi-Garcia (2019) shows that the effects of technological improvements are intrinsically related to the level of uncertainty. There is ample empirical evidence suggesting that uncertainty stemming from macroeconomic and financial sources closely correlates with the state of the economy and heightens during recessions.[7]

To summarize, it is reasonable to posit that granting identical patents in different states of the world may lead to significantly different reactions from the economy, which is what we focus on next.

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

We now turn to our analysis of whether innovation shocks affect aggregate variables differently in expansions or recessions. Specifically, we expand the linear model from Equation (1) to a state-dependent setup, given by

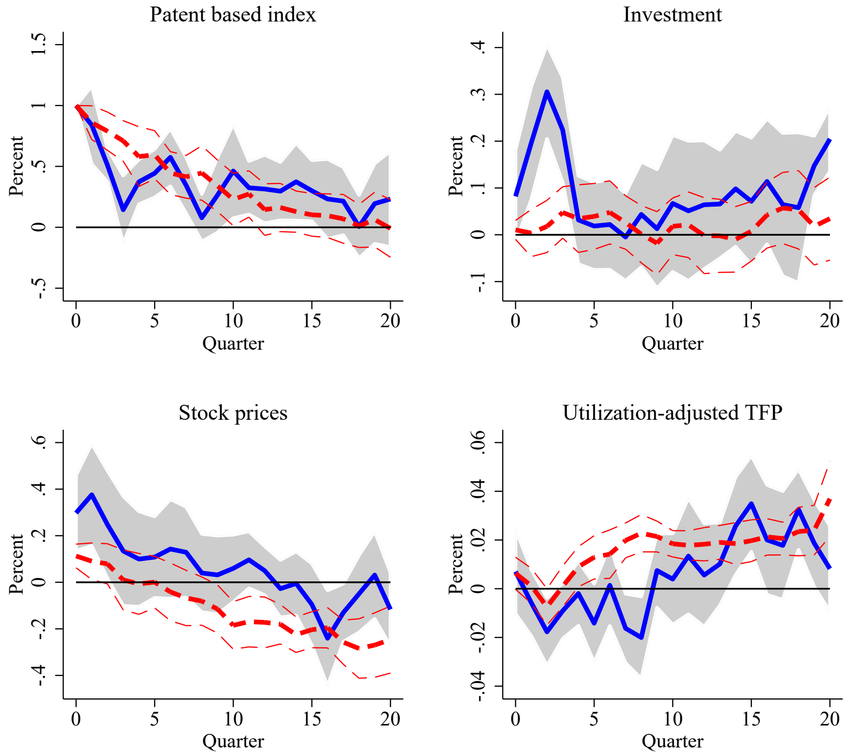
$$z_{t+h} = I_{t-1}\left[\alpha_h^A + \psi_h^A(L)y_t + \beta_h^A x_t\right] + (1 - I_{t-1})\left[\alpha_h^B + \psi_h^B(L)y_t + \beta_h^B x_t\right] + \varepsilon_{t+h}, \qquad (2)$$

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 economy by relying on NBER-dated recessions and expansions, and the dummy takes a value of 1 when we are in a recession and the complement otherwise. Here, β_h^k represents the response of variable z_t at horizon h in state $k \in [A, B]$ representing recessions and normal times, and it measures the average effect of the shock based on the initial state and embeds the average effect of the shock for a possible change in the state. We allow all coefficients to change based on the state of the economy, nesting the case of all coefficients being linear.

Figure 3 presents the state-dependent impulse responses after an innovation shock,

[7]See, for example, Fernández-Villaverde and Guerrón-Quintana (2020) and Cascaldi-Garcia, Sarisoy, Londono-Yarce, Datta, R.T. Ferreira, Grishchenko, Jahan-Parvar, Loria, Ma, Rodriguez, Zer, and Rogers (2023).

Figure 3 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.

comparable to the linear version presented in Figure 2. Blue solid lines are the responses of stock prices, utilization-adjusted TFP, and investment to an innovation shock across recessions defined as NBER recessions, while red dashed are responses in tranquil times.

The comparison of the responses in recessions and tranquil 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 good 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 tranquil times, indicating that the 1% increase in the patent-based index is anticipating the same level of future productivity. However, during tranquil 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 tranquil times.

Considering the two opposing forces faced by the firm during recessions, this empirical evidence 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.

Overall, we conclude that patent-based innovation shocks propagate differently through the economy during recessions compared to expansions, where they have a substantially higher impact on aggregate private investment.

3.4 Cyclicality of Patent-Based Innovation Index

A possible concern when examining the relationship between innovation and economic conditions is whether innovative actions, and not its economic outcomes, differ between economic expansion and recession periods. Specifically, it is essential to determine if innovation, particularly patenting activity, is more or less prevalent during economic expansions. If this is the case, any asymmetric effects following innovations may result from endogenous responses to the business cycle rather than inherent characteristics of innovation or differential behavior of agents based on their expectations of future outcomes from innovation in different economic states.

As discussed in Section 2, we identify patent-based innovation shocks using high-frequency stock market changes of the firms around a narrow time window of patent grants. While the firm chooses the timing of a patent application, the grant date contains an element of randomness. For example, the median delay between patent application and issuance is approximately three years, which means that a firm might submit an application in an expansion and receive the grant in a recession, or vice-versa. However, the firm could also apply and receive a positive outcome during the same phase of the business cycle, with this scenario being more likely in an expansion due to its longer duration. We exploit the randomness in the patent issuance process, in addition to the information in the patent-based innovation index, to investigate how the economy responds to innovation shocks in different states of the economy.

We also examine the relationship between common measures of innovative activity and real GDP at business cycle frequencies, extracted using both Hodrick-Prescott filter and band-pass filter with frequencies between six and forty quarters as outlined in Table 1. Our analysis reveals that R&D spending, an often-used indicator of innovative activity, significantly correlates with real GDP at business-cycle frequencies. The correlation almost doubles at medium-cycle frequencies, which are from forty to eighty quarters (not shown). However, 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, both extracted using the HP filter and band-pass filter.

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

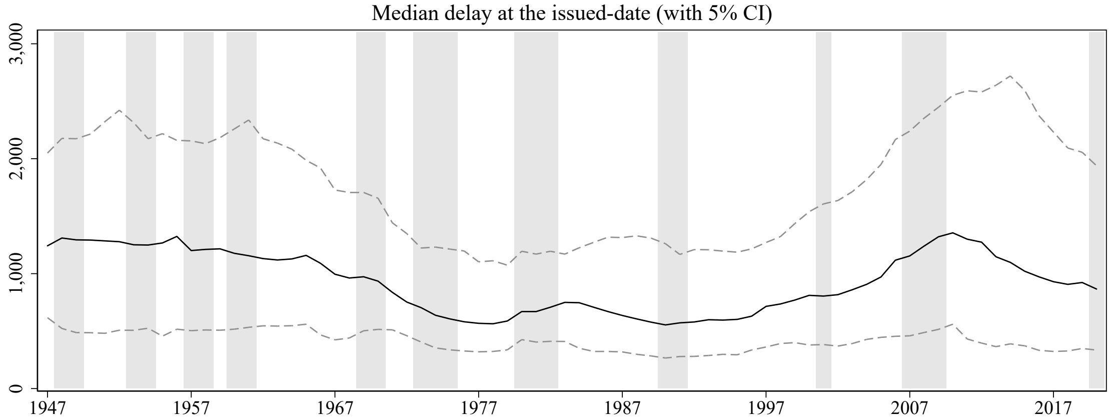
Note: Business-cycle frequencies are extracted using the Hodrick and Prescott (HP) filter with a parameter value of $\lambda = 1600$ (column 1), as well as a band-pass filter with frequencies ranging from 6 to 40 quarters (column 2).

Based on the evidence discussed above, we draw two key conclusions. First, the cyclicality of R&D spending suggests that using it as a proxy for innovation activity may lead economic agents and econometricians to misinterpret business cycle movements as a consequence of innovation, when in fact they may be confounded by other economic factors such as credit availability, financial constraints, risk aversion, uncertainty, and monetary or fiscal policies. Moreover, any analysis of the state-dependency of shocks to R&D spending may also confound potentially different economic effects in recessions and expansions with other cyclical factors that are state-dependent.

Second, the lack of cyclicality in patent applications and grants implies that while firms may choose to invest more in R&D during economic expansions, the actual outcome of innovation, as measured by patenting activity, is unrelated to the business cycle. This evidence supports the argument that real innovative ideas are hard to find (Bloom, Jones, Van Reenen, and Webb, 2020), and their occurrence and subsequent patenting activity are independent of the state of the economy. Furthermore, this observation is important for distinguishing cyclical factors unrelated to patenting from actual innovative activity. However, it is worth noting that the number of patent applications or grants does not account for the quality of the innovation or its potential impact on future productivity.

Another potential concern regarding the number of patents is whether the lag between patent application and issuance exhibits cyclicality, even if the applications and grants themselves do not. However, as illustrated in Figure 4, which depicts the median delays (in days) between patent application and eventual issuance, the lag has remained relatively stable over time, with an average of 908 days since 1947. Furthermore, as indicated

Figure 4 MEDIAN DELAYS (IN DAYS) BETWEEN PATENT APPLICATIONS AND ISSUANCE



Note: The x-axis shows the year that the patent is issued.

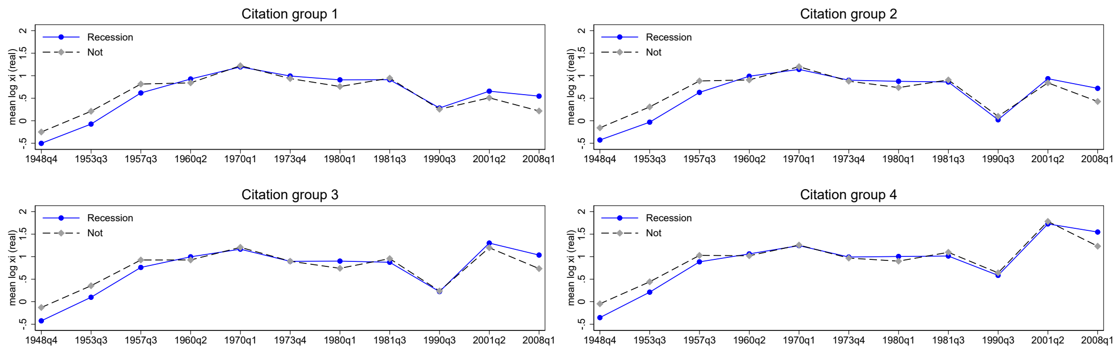
in Table 1, there is no significant correlation between the lag time and GDP, effectively ruling out the possibility of cyclicality.

Finally, the patent-based innovation index developed by Cascaldi-Garcia and Vukotić (2022) exhibits a low correlation with GDP, suggesting mild cyclicality. This mild positive correlation may be due to the normalization approach used to construct the index or due to the market fluctuations surrounding patent grants. There are three alternative explanations for this observation. First, as the patent-based index is scaled by aggregate GDP, the denominator may be carrying the cyclicality and, consequently, the state-dependent effects. However, the asymmetric response of aggregate investment to an innovation shock, shown above, carries over also when we use patent-based innovation index scaled by total market capitalization rather than GDP.

Alternatively, the mild cyclicality may stem from the patent-based innovation index itself, where economic agents may react slightly more positively to patent activity during expansions due to the innovation's inherent economic potential (fundamental) or increased optimism (non-fundamental). We test this hypothesis directly below. Lastly, the positive correlation may reflect the short-run endogenous response of GDP to the market-implied innovation, as part of the economic effects of the innovation may already be realized in the short term. Both possibilities align with the notion of an expectation-driven business cycle technological shock, as described by Beaudry and Portier (2006). To address potential identification concerns, we account for potential cyclicality effects by including lagged GDP as a control variable in all of our analyses.

In order to directly address whether the stock market reacts to similar innovations differently across recessions and normal times, we consider the average stock market valuation of patents across the 11 different recessions in our sample period and the corresponding windows of normal times around them. In order to compare similar scope of discovery, we divide the patents by their forward citations, that arguably indicate their scientific value, into quartiles for each relevant recession, given that patents accumulate more citations over time. Figure 5 shows the average real stock market valuations of the patents released during a given recession (blue dot) with the corresponding average stock market valuation in a window of 8 quarters before and after the recession (grey dots), for a given group of citations. There seems to be no evidence of stock markets having a systematically larger or smaller response in recession.[8] The recession valuation (grey dots) lie above the valuation of similar patents in normal times (blue dots) at times, like in the early part of the sample, and below that at times, like in the 2000s.

Figure 5 Average real market valuation across states of the economy



Note: The figure shows the average real stock market valuation for a given recession (blue dots with solid lines) and the corresponding window of 8 quarters preceding and after it (grey dots with dashed lines). In recessions (blue solid) for a given citation group, which indicates the four quartiles of citations in a given 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 is significantly different for patents issued in recessions relative to normal times. Similar to Kogan et al. (2017), we relate the total number of citations C a patent j receives in the future to the estimated market value of the patent, ξ_j, and additionally consider both a recession dummy, R_j which takes a value of 1 if the patent is issued in a recession and is 0 otherwise, and then an interaction term of recession with the forward citations.[9]

$$\xi_j = a + b\,\text{Citations}_j + c\,R_j + d\,(R_j \times \text{Citations}_j) + f\,Z_j + u_j \tag{3}$$

In order to account for factors that may influence citations and the measured patent valuations, we include a vector of controls Z that includes grant-year fixed effects, because

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

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

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

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 consider a different sample than Kogan et al. (2017), which is extended to 2019, and verify their finding of a positive association between forward citations and patent market values. However, as displayed in Table 2, there is no strong statistical evidence that patent market values are different if the patent is issued in a recession, and also this relation between forward citations and patent values is not significantly different in the case that the patent is issued in a recession.

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.

In our analysis, we rely on quarterly financial data from the Compustat database, which provides detailed balance-sheet and income-statement information for all publicly traded firms U.S. 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. The appendix provides detailed information on the construction of these variables. Our baseline sample covers the period from 1966:Q1 to 2019:Q4.[10]

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, which are likely to be more affected by changes in stock market valuations resulting from innovation.

Furthermore, 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. (2019). Therefore, by leveraging the 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.[11] Once again, x_t is the patent-based innovation index, and the coefficient β_h gives the response of the variables of interest z_t to an innovation shock. Here y_t is a vector of aggregate-level controls which include variables mentioned above in our aggregate specification, and we consider two lags of these variables. In addition, we also consider firm-level control variables in the vector F_{jt}, which includes firm sales growth and current assets as a share of total assets.[12]

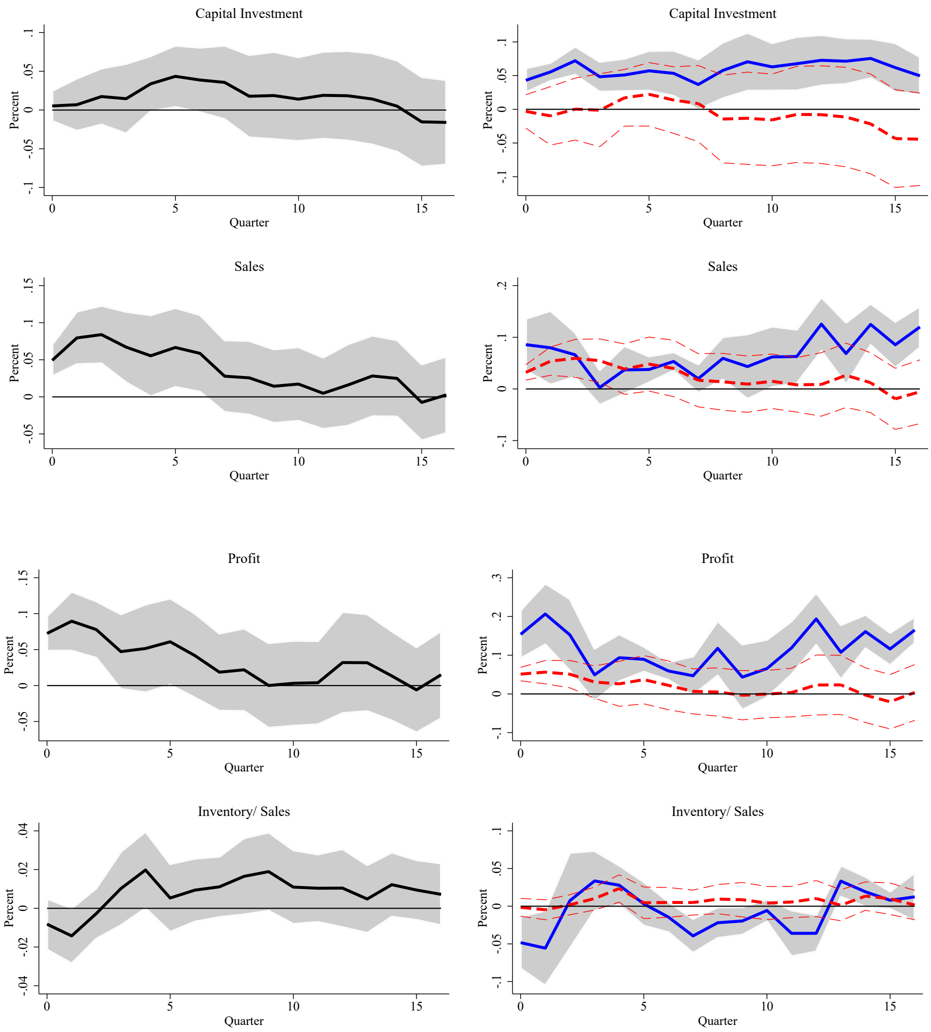
[10] It is worth noting that the availability of data for different firm-level variables may vary. For example, data for R&D spending is regularly available in the sample from mid to late 1980s.

[11] 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.

[12] The baseline specification shown in Figure 6 abstracts from these firm level controls, F_{jt}, but results in Appendix Figure A.5 show that the broad results are unchanged with the inclusion of these controls variables. This is also true for the state dependent specification.

We also consider other balance sheet variables like leverage, liquidity, and size based on assets in the next section. We cluster standard errors two ways to account for correlation within firms and within quarters.[13]

Figure 6 Firm-level Analysis: Average effects of patent-based innovation shocks (left) and state-dependent (right)

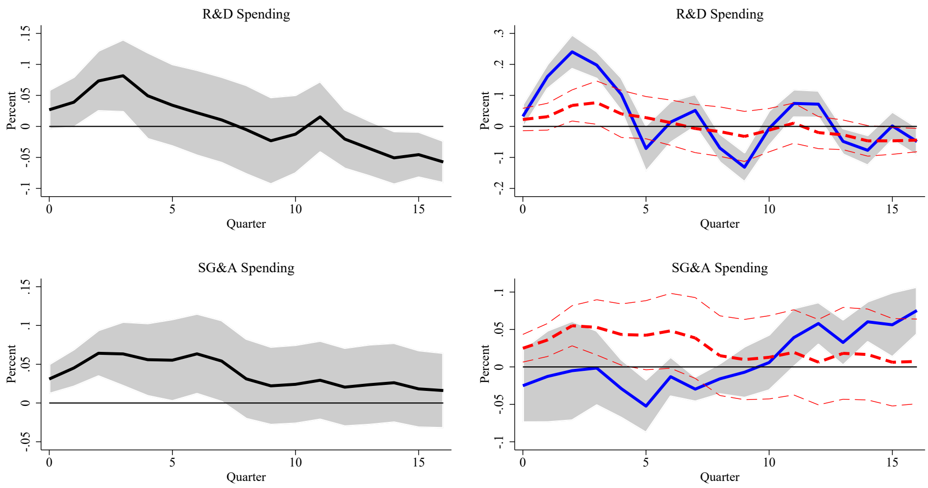


Note: In recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown.

The left panel of Figure 6 shows the average response of select firm-level variables to the aggregate patent-based innovation shock. In response to this shock, firm-level investment in tangible capital increases on impact and peaks about seven 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. Consistent with these

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

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



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

models, we also see that the inventories-to-sales ratio falls on impact as firms run down inventories relative to sales when the shock hits the economy. This result is in line with Vukotić (2019), who also finds that the inventories-to-sales ratio of the manufacturing sector falls ahead of future technological improvements. 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.[14] In addition to tangible capital, our analysis also indicates that firms increase investment in non-tangible capital, such as research and development (R&D) spending and selling, general, and administrative (SG&A) expenses, as shown in the left panel of Figure 7.

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

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

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 the same as Equation 4.

The right panel of Figure 6 shows the responses of the firm-level variables to the aggregate patent-based innovation shock in recessions (solid blue) and expansions (red dashed). In response to this innovation shock, firm-level capital investment increases sig-

[14]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.2 in the Appendix. Other components of consumption have a more muted response.

nificantly more during recessions than expansions. Moreover, although capital investment initially rises in good and bad economic times, the increase is more persistent and larger 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 expansions 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 bad times. The inventories-to-sales ratio falls both during good and bad times, but this fall is greater when the innovation shock hits in a recession.

Taking together, the empirical evidence presented in Figure 6 emphasizes that innovative actions occurring in bad times come with an opportunity to grow that demands fast production adaptations, not only in terms of incentivizing firms to invest in modernization of the production plants, but also by creating a higher incentive to sell their current products and deplete inventories originated from potentially older technology.

Turning to the right panel of Figure 7, and the responses of intangible capital investment, we observe an interesting and clear difference in the response of R&D and SG&A spending in good and bad times. Both SG&A and R&D spending are considered as intangible capital, but we can further distinguish between them as innovation and non-innovation related spending. 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 spending in response to the shock, while the rise is statistically insignificant during good times. On the other hand, SG&A spending declines in response to the shock during recessions, but rises during expansions, suggesting that firms cut back on administrative capital spending in recessions.[15]

As R&D is viewed as a major source of economic growth, its behavior in the immediate aftermath of innovation shocks is worth further discussion. As shown in Section 3.4, aggregate R&D spending data is procyclical. While at odds with the Schumpeterian notion that recessions are opportune times for investing in relatively cheaper, growth-enhancing activities, several researchers have attempted to provide theoretical explanations for such procyclicality.[16] Our findings, however, lend additional empirical support to the original Schumpeterian notion of innovation opportunity in recessions. Specifically, we observe

[15] 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.

[16] 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.

that firms tend to increase their spending on innovation-related R&D and reduce spending on non-innovation-related SG&A activities in response to favorable innovation shocks during recessions. This empirical result aligns 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 have provided rich firm-level evidence on the response of firm decisions to aggregate innovation shocks. Notably we have shown that the response of firm capital investment is larger in recessions than in expansions, which is consistent with the response of aggregate private investment. We explore the transmission mechanism in the following section.

4.2 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.

We aim to investigate which type of firm characteristics help explain the increase in investment in physical capital by firms in response to an innovation shock. As our analysis relies on within-firm variations, we utilize data from the sample period after 1984, when consistent information for a sufficiently large number of firm characteristics and variables becomes available. This sample period also aligns with previous studies such as Cloyne et al. (2019) and Ottonello and Winberry (2020), who analyze transmission mechanism of monetary policy shocks.

In particular, 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} is firm-level capital investment, x_t is the patent-based innovation index, y_t are aggregate level control variables and for each firm characteristic f_{jt}, we consider $(f_{j,t-1} - E[f_{jt}])$, which is the deviation of the firm characteristic from the average of f_{jt} for firm j in the sample, and then standardized over the entire sample. This strategy captures within-firm variation in the variable of interest, similar to Ottonello and Winberry (2020).[17] The

[17] By demeaning the characteristics within firms, our estimates capture how a given firm responds to the shock when the given characteristic is higher or lower than usual. If instead we interact the firm characteristic with the shock, then our results would be partly determined by permanent differences in responsiveness across firms that are different across those characteristics. When we consider across-firm variation, i.e. do not demean within firms but across firms, we reassuringly get very similar results.

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 3.4.

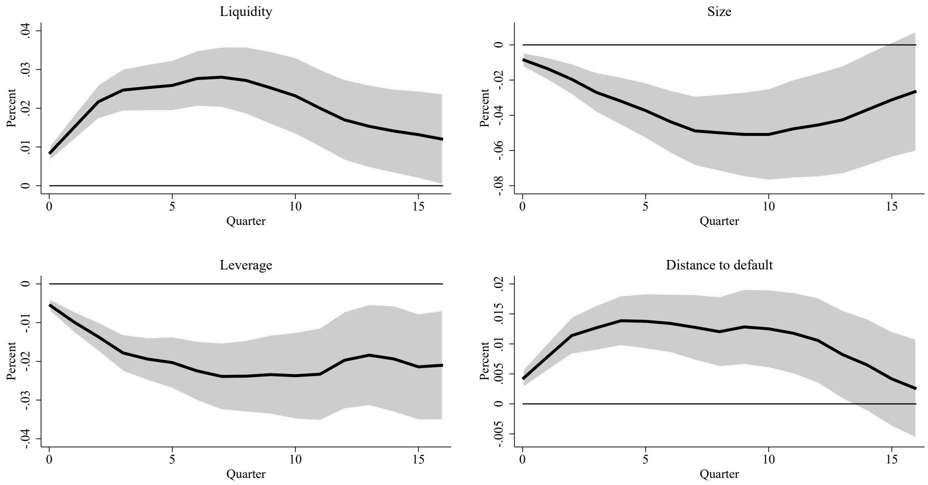
Drawing motivation from the literature that has emphasized the role of financial constraints in the transmission of macroeconomic shocks, we examine the relationship between financial frictions and firm investment behavior in response to innovation shocks. In particular, we investigate how firms with different levels of financial health respond to innovation shocks and how the state of the economy influences these responses. We consider multiple measures of financial frictions, including firm size, leverage, liquidity, and distance to default, to better understand how these factors may shape firms' investment responses to innovation shocks.

Although the evidence presented in the previous section suggests that firms tend to increase capital investment in response to favorable innovation shocks more during recessions, it does not necessarily imply that financial constraints do not matter for the transmission of innovation shocks. Financially constrained firms may be unable to respond to these shocks, with financially resilient firms driving the observed investment behavior. This suggests that financial constraints may still play a role, as many constrained firms may not be able to increase investment in response to favorable innovation shocks.

In order to investigate whether financially constrained firms respond differently to innovation shocks, we estimate different versions of specification (6) using various measures of financial constraints as firm characteristics. The four measures—liquidity, leverage, distance to default, and firm size—capture different aspects of a firm's financial health and constraints. Liquidity measures a firm's ability to meet short-term financial obligations and has been highlighted recently 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, on the other hand, is a measure of credit risk that estimates the probability of default based on a structural credit risk model proposed by Merton (1974), which takes into account market value of equity, volatility of equity, and face value of debt. Firm size, here captured by total assets, has been a traditional (but imperfect) proxy for financial constraint since Gertler and Gilchrist (1994), given that smaller firms are usually more financial constrained than larger.[18]

[18] 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

Figure 8 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 8 shows the coefficient on the patent innovation index interacted with the standardized firm characteristic under consideration.[19] 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 the typical firm level liquidity. In addition to firms with higher liquidity, firms with higher distance to default show a stronger response of investment to innovation shocks. Conversely, firms with higher leverage exhibit a lower responsiveness of investment to innovation shocks. Taking together, these results suggest that less financially constrained firms, i.e. with high liquidity and distance to default and low leverage, are more responsive to innovation shocks, and the shocks propagate through higher investment responses of these firms. Finally, the results for firm size suggest that smaller firms respond with larger capital investment. This result should be read with caution as, while smaller firms are indeed more financially constrained than larger,[20] these are also the fastest growing firms. In addition, recent evidence from Crouzet and Mehrotra (2020) shows that investment of small firms tends to be more sensitive to the business cycle than for large. 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 8, with lower capital investment response the larger the

and Zakrajšek (2012).

[19]The results shown in Figures 8 and 9 hold qualitatively and even 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.6 in the Appendix.

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

firm is, indicates that the larger sensitivity channel dominates the financial constraint when analyzing the response based on firm size.[21]

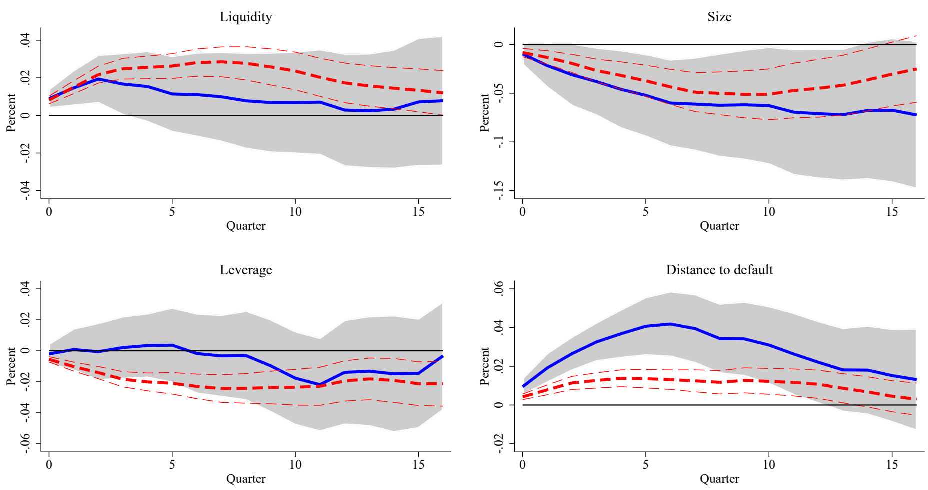
Next we consider if these firm characteristics that serve as proxies for financial constraints also play a role in explaining our firm-level state-dependent results, driving the larger response of firm investment in recessions.

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 tranquil times.

Figure 9 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.

When we consider firm leverage and liquidity, we do not find a statistically different role in explaining the investment response of the firm across recessions and expansions, as shown in the various panels of Figure 9. However, this is not the case when we consider distance-to-default. The last panel of Figure 9 provides evidence of state-dependence in

[21] The results are robust to alternative definitions of variables. Figure A.7 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.

the propagation mechanism based on distance-to-default, and shows that these effects are even more pronounced during recessions. Specifically, during periods of economic downturn when financial constraints tend to be tighter, we observe that firms with higher distance to default are more responsive to favorable innovation shocks, and increase their capital investment to a larger extent. This finding suggests that the propagation of innovation shocks through less financially constrained firms is even more pronounced 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 different in the firm investment response across the state of the economy, above and beyond other characteristics such as liquidity and leverage is perhaps 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. This role of borrowing ability is particularly critical and amplified during recessions

Finally, the upper-right panel of Figure 9 also indicates no statistical difference between investment response in recessions and expansions, when controlling for firm size. Considering that recessions are indeed periods of higher financial constraint than expansions, 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.

5 Conclusion

This paper investigates how innovation shocks propagate through the economy and provides extensive empirical evidence using aggregate and firm-level data. In order to identify aggregate innovation shocks, we adopt a novel approach proposed by Cascaldi-Garcia and Vukotić (2022) who use firm-level changes in stock market valuations triggered by news about patent grants.

Our findings suggest that the timing of these news matters. In response to an aggregate patent-based innovation shock, the aggregate economy exhibits a stronger response during recessions than expansions, primarily driven by private investment. Motivated by this evidence, we further investigate by analyzing firm-level data.

Using rich microdata on publicly listed U.S. firms, we show that following a favourable innovation shock, firms with lower default risk invest significantly more than those with high default risk. Moreover, the difference between the two types of firms is significantly more pronounced during bad times. In particular, innovation shocks – which amount to receiving good news about patent grants – elicit a stronger reaction from financially healthy firms during bad times.

Our results support the idea that recessions represent ideal times for investing in growth-enhancing activities. At the same time, however, our results emphasize the importance of financial frictions in the transmission of innovation shocks, as financially unconstrained firms drive our results.

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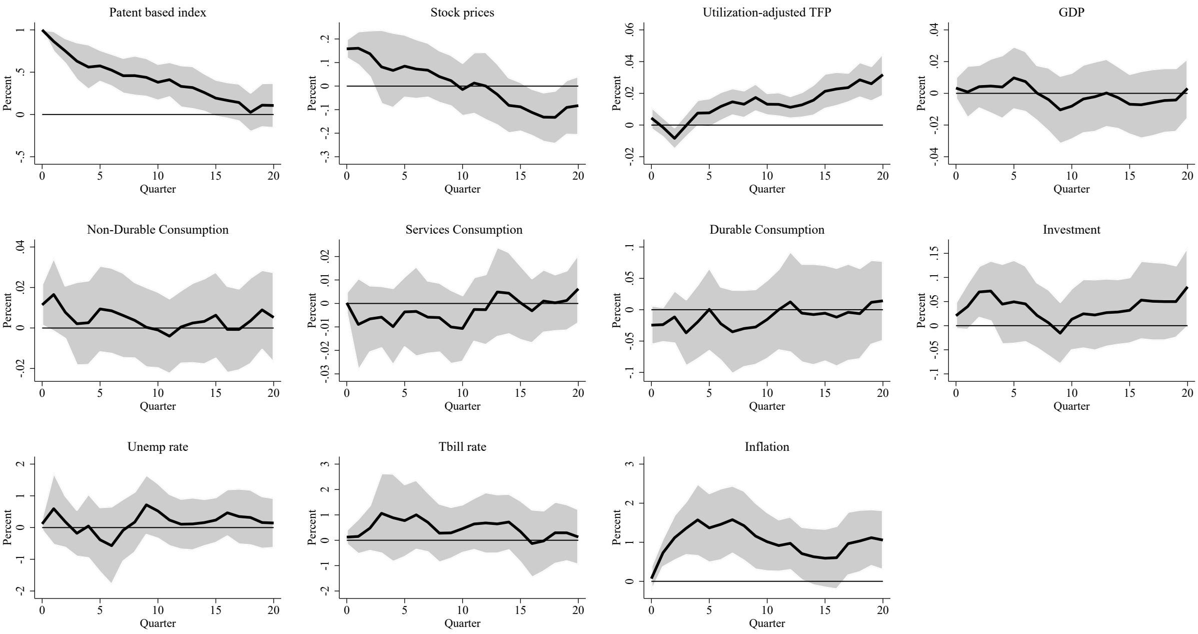
A Appendix

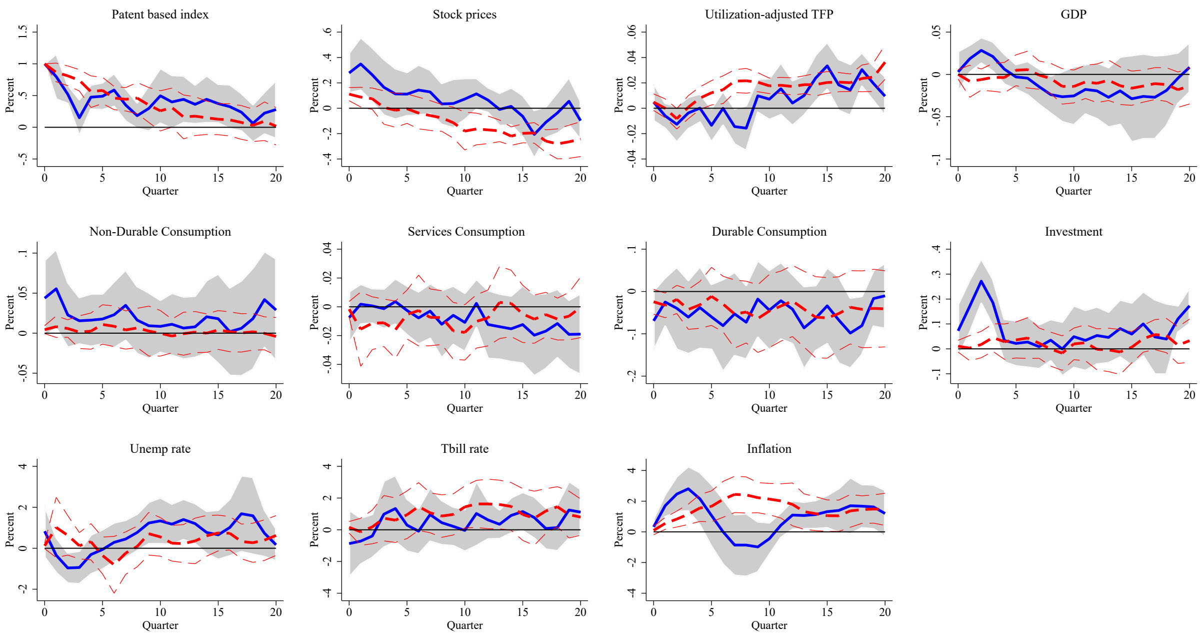
A.1 Aggregate Effects of Patent-Based Innovation Shocks

Figure A.1 Aggregate Analysis: Linear effects of patent-based innovation shocks - Additional Variables



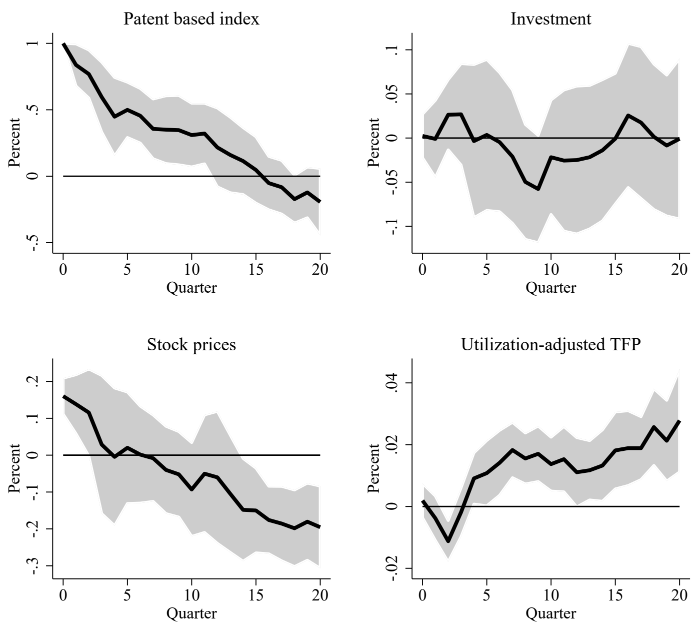
Note: Corresponding 90% confidence bands shown. Sample period: 1947-2019.

Figure A.2 Aggregate Analysis: State-dependent Effects of Patent-Based Innovation Shocks - Additional Variables



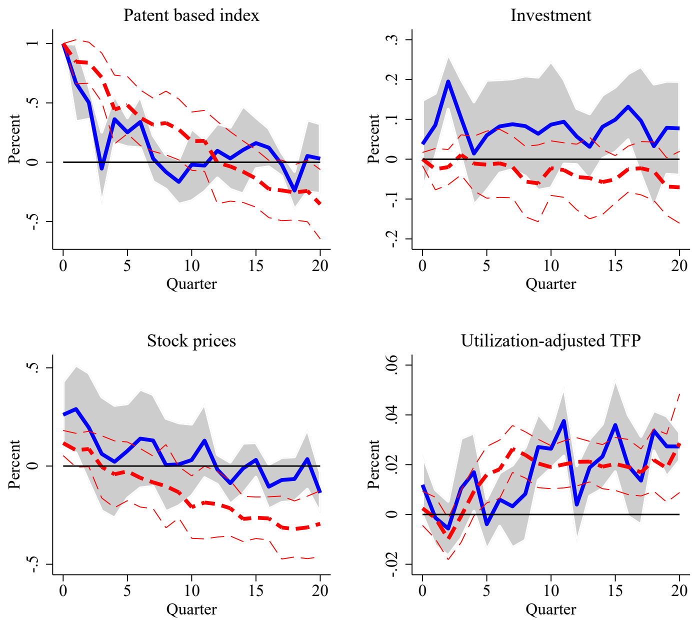
Note: in recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown. Sample period: 1947-2019.

Figure A.3 Aggregate Analysis: Linear effects of patent-based innovation shocks - Shorter sample



Note: Corresponding 90% confidence bands shown. Sample period: 1966-2019.

Figure A.4 Aggregate Analysis: State-dependent effects of patent-based innovation shock s- Shorter sample



Note: in recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown. Sample period: 1966-2019.

A.2 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.

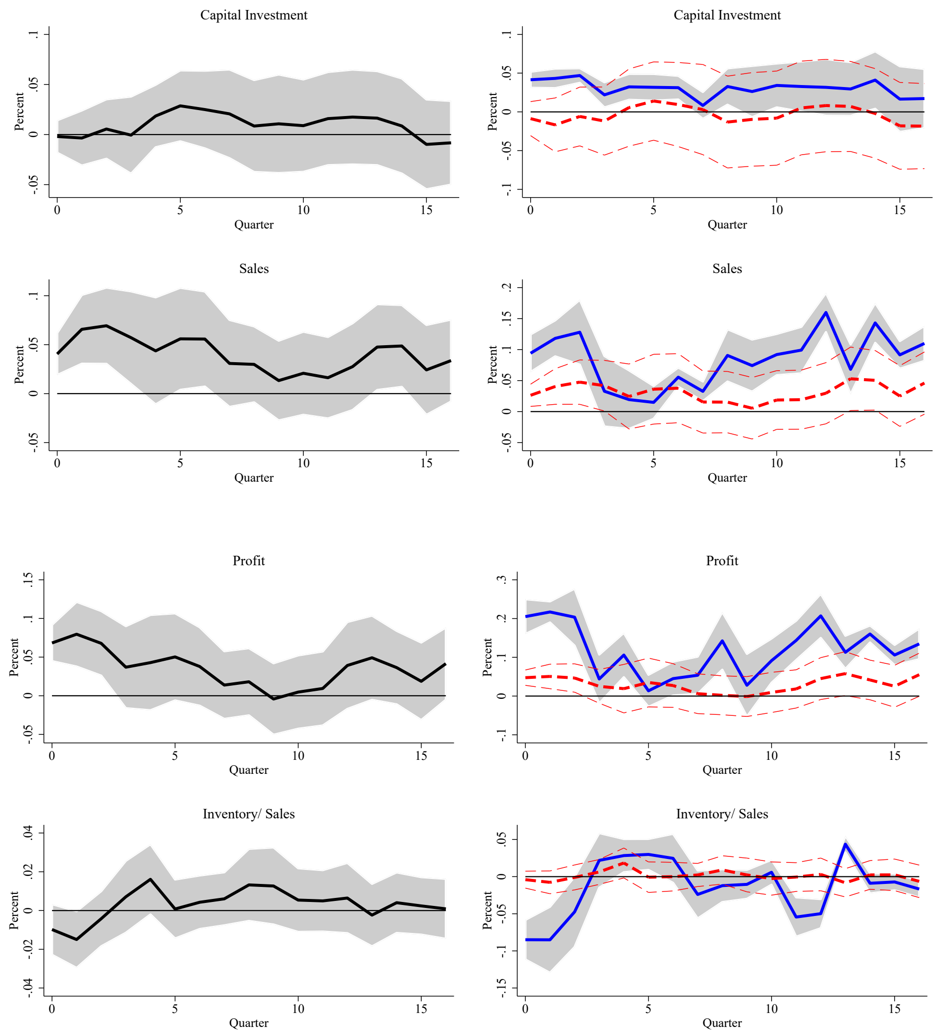
We transform all these series into per capita values by dividing them by the BLS series of the civilian noninstitutional population over 16 (LNU00000000Q), and real by deflating by the GDP deflator.

- 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).

Table A.1 Firm-Level Variable Definitions

Variable	Compustat Variable	Variable Description
Capital Stock	ppegtq, ppentq	Property, Plant and Equipment - Total (Gross) and (Net) Ottonello and Winberry (2020)
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

Figure A.5 Firm-level Analysis: Average effects of patent-based innovation shocks (left) and state-dependent (right) - Additional firm level controls in Equation 4 and 5



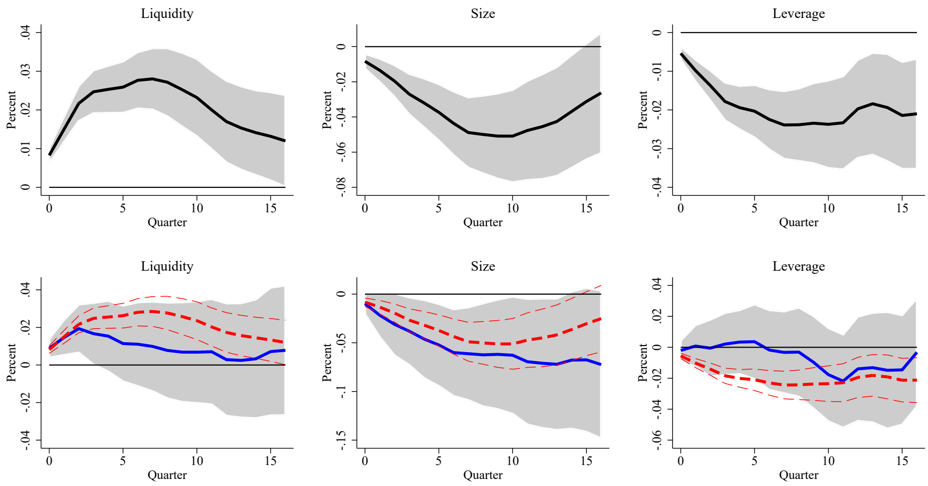
Note: In recessions (blue solid) and normal times (red dashed). Corresponding 90% confidence bands shown.

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

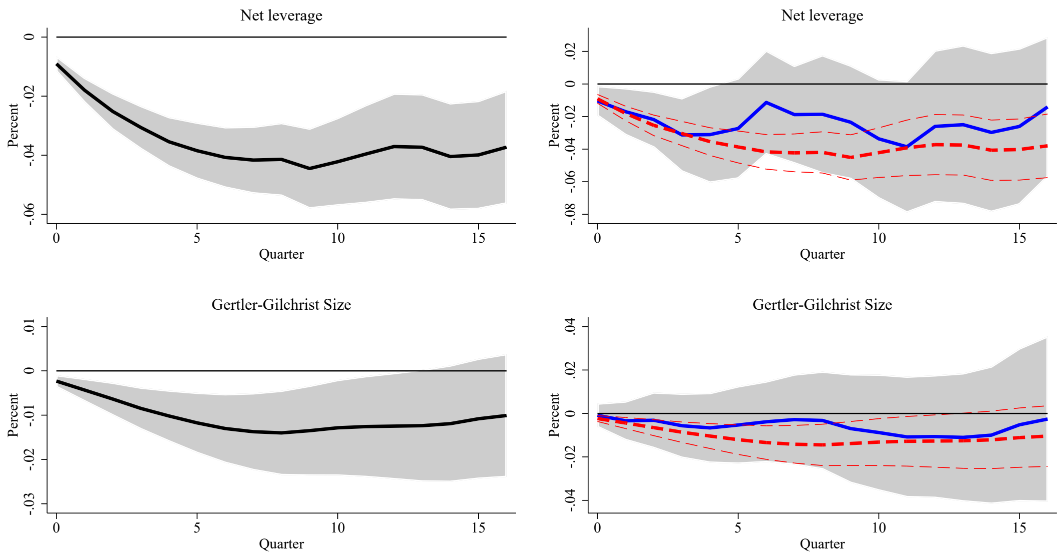
This table shows the correlation matrix of the firm characteristics from 1985q1-2019q4. Leverage is ratio of total debt to total assets. Liquidity is the ratio of cash and short term investments to total assets. Size is given by total assets of the firm. Net leverage is the ratio of total debt minus 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.

Figure A.6 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.7 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.