Firm liquidity and the innovation channel of monetary policy *

Changseok Ma †

University of Texas at Austin

This draft: August 27, 2023
First draft: October 13, 2022

PRELIMINARY
For the latest version click here

Abstract

I provide new empirical evidence against long-run monetary neutrality and document where this non-neutrality originates: innovation. Expansionary monetary policy shocks increase the value of innovation and lead firms to develop new patents. As a result, even transitory monetary policy shocks affect the long-run level of total factor productivity (TFP). This channel is driven empirically by firms with high liquidity: cash-starved firms are unable to finance higher innovation. To explain these empirical findings, I develop a model of heterogeneous firms with cash-in-advance constraints, which predicts that firms with higher liquidity are more responsive to expansionary monetary policy shocks while innovation of firms with lower liquidity is held back by binding constraints.

Keywords: cash-in-advance constraint, endogenous technology, firm balance sheets, monetary policy

*I am very grateful to Saroj Bhattarai, Christoph Boehm, and Olivier Coibion for their invaluable guidance and support. I thank Stefano Eusepi, Clemens Sialm, as well as seminar participants at UT Austin, AMES2022, MMF2022, MEG2022, MMM2022, SEA2022 for helpful discussions and suggestions. I thank Eric Swanson for sharing data with me.

†Email: changseok.ma@utexas.edu

"The most important factor determining living standards is productivity growth ... Federal Reserve actions to strengthen the recovery may not only help bring our economy back to its productive potential, but it may also support the growth of productivity and living standards over the longer run." – Janet Yellen

1 Introduction

Is money neutral in the long run? It is a near-universal feature of modern macroeconomic models that monetary policy affects real outcomes only in the short run. This assumption is often embedded in the model by treating productivity as exogenous; thus, the central bank cannot affect productivity by construction. Recent work has begun to question this assumption: Moran and Queralto (2018) and Jordà, Singh, and Taylor (2020) present findings that contradict the concept of long-term monetary neutrality. Expanding on their findings, I offer fresh evidence that goes against the notion of long-term monetary neutrality and, importantly, identify one channel that can explain this finding: endogenous innovation decisions on the part of firms. As a result, my results support Yellen's hypothesis that monetary policy actions can matter not just for stabilization purposes but also in promoting long-run productivity.[1]

Prior work has speculated about the potential sources of a productivity effect of monetary policy shocks. However, little is empirically and quantitatively known about the innovation responses of firms due to the lack of detailed data on firms' innovation measures. My main innovation is to break through this data logjam by constructing firm-level innovation measures based on their patent applications.

A sizable body of new literature (Kogan et al., 2017; Bluwstein, Hacioglu Hoke, and Miranda-Agrippino, 2020; Cascaldi-Garcia and Vukotić, 2022) shows the causal relationship between patent applications and productivity which implies that patent applications can be considered a proxy for success in creating knowledge capital, making it an ideal measure to achieve the goal of this research. Using the patent history data that includes detailed information on new technologies and identified monetary policy shocks, I examine the following two questions: 1) Does monetary policy affect innovation? 2) If so, which firms are the most responsive to shocks in terms of innovation? In answering these questions, I emphasize the role of innovation in explaining the productivity effect of monetary policy shocks and explain the heterogeneity across firms in terms of how their innovation responds to unexpected changes in monetary policy.

To do so, I first provide aggregate- and firm-level empirical evidence using local projections

[1]The most recent example is Benigno and Fornaro (2018); Fornaro and Wolf (2020); Garga and Singh (2021); Galí (2022); Acharya et al. (2022)

proposed by Jordà (2005). From the aggregate point of view, I first revisit previous findings as proposed that expansionary monetary policy shocks increase long-run TFP. After a one standard deviation expansionary monetary policy shock, TFP grows by 1.5% after 24 quarters.[2] Then, I present evidence that the shock gradually and eventually stimulates aggregate innovation as measured by new patent applications by 2%. The sluggish response of innovation assures that the innovation responses after the shock arises from inventing rather than patenting an old technology.[3] Unconditionally, innovations generally precede observed changes in TFP by 1-2 years, and this timing delay is consistent with what I observe in my conditional impulse responses.

Why does innovation rise after expansionary monetary shocks? I show that the economic value of patents rises sharply after interest rates fall, consistent with a lower discounting of future payoffs to innovation. I use the economic value of each patent as proposed by Kogan et al. (2017). My findings demonstrate that the estimated effect of expansionary shock on patent value is *large*; a one standard deviation of expansionary shock leads to 20% growth in the value of patents. Previous works relying on a theoretical model, such as Moran and Queralto (2018), show that expansionary monetary policy shocks increase the value of new technology. However, their effect is smaller than I find in this paper.[4] Such a large response can be explained by a persistent drop in the discount rate. In addition, the cyclical upswing after expansionary monetary policy shocks can also be a source of fluctuation in the market value of the new patent because it will boost the profits from patenting new technology. I also find that, as the level of innovation rises with the arrival of new patents, the economic value of patents eventually returns to its steady-state. In other words, the temporarily high return to innovation leads to a permanent increase in the level of technology, which can account for the positive long-run TFP response to an expansionary monetary policy shock.

Second, motivated by the aggregate evidence, I perform a firm-level analysis to clarify the mechanism underlying the effect of monetary policy shock on innovation. Specifically, I provide cross-sectional evidence using the data on firms' patent stocks, constructed based on detailed information on patents. To precisely estimate the effects of monetary policy shocks depending on firms' characteristics, I control for a variety of firm-level variables which have already been documented to be important in explaining the heterogeneity of tangible capital responses in previous literature. Among them, I find that liquidity plays a critical role in understanding the heterogeneity; a one standard deviation higher level of liquidity leads to 1.5 percentage points more growth in innovation after a one standard expansionary monetary policy shock. The estimates are statistically

[2] A one standard deviation monetary policy shock raises the effective federal fund rate by 30 basis points.

[3] Meier and Reinelt (2020) show the sluggish response of R&D after monetary policy shocks. They conclude that such response in R&D cannot explain the TFP changes within 2-3 years after monetary policy shocks.

[4] Moran and Queralto (2018) reports 60 basis points of expansionary monetary policy shocks to raise the value of innovation around 1%.

significant and economically sizable, and the difference across firms persists even six years after the shock.

Third, the reason why firms with high liquidity are the most responsive to the shock is neither because their patents appreciate more in value nor because they rely more on external borrowing. Rather, cash itself plays a key role in financing investment in intangible capital. In the literature, financial constraints are considered one of the main drivers of fluctuations in tangible capital (Ottonello and Winberry, 2020; Howes, 2021). Internal financing from past cash flows is typically considered to be an alternative to external borrowing. However, when it comes to intangible capital, the role of liquidity becomes important. This is because the problems of "asymmetric-information" and "moral-hazard" are expected to raise the costs of obtaining finance from sources external to the firm (Hall, 2010). Moreover, firms cannot raise debt financing for intangible capital because it is not collateralizable (Falato et al., 2020). In this paper, I employ firms' borrowing data and find that there is no heterogeneity in firms' borrowings after monetary policy shocks, which suggests that borrowings cannot be a source of heterogeneity in innovation. This finding is also confirmed by survey evidence. I use the responses of chief financial officers to open-ended survey questions on why their company's investment would be insensitive to fluctuations in borrowing cost: if a firm schedules R&D for the next 12 months, it becomes insensitive to changes in interest rates, and this effect does not change with liquidity concerns.[5]

The empirical findings therefore indicate that monetary policy shocks affect aggregate innovation, the source of fluctuation in long-run TFP, and emphasize the role of liquidity in transmitting these shocks to innovation. To interpret the empirical results, I develop a dynamic model of innovators' cash holdings, borrowing decisions, and decisions to invest into intangible capital. As the number of varieties is the measure of aggregate technology in the Romer-style endogenous growth model, I assume that innovation takes a form of the total amount each innovator produces. One of the key innovations in the model is the cash-in-advance constraint, which generates a motive for cash holding. Innovators can only make an investment that is less than the amount of cash they hold and the amount they borrow through intra-period loans at the beginning of the period. Because borrowing is accompanied by underwriting fees and intangible capital has low collateral value, firms would want to avoid tapping into the credit market to finance their investments. To capture the heterogeneity in innovation responses depending on the level of liquidity, I define three aggregate states of the economy in the model: low-, middle-, and high-interest rates. Each state determines the real price of an invention, real interest rate, and real wage, and I assume that there is a one standard deviation of monetary policy shock between each state. Based on the empirical findings, unexpected changes in the interest rate affect the price of an invention, real wages, and the

[5] This result is opposite to what Jeenas (2019) finds in his paper, which is that liquidity dampens the effect of monetary policy shocks on tangible capital, while liquidity amplifies the effect of the shock in this paper. I discuss this more in detail in Section 4.

real interest rate accordingly. In this setting, expansionary monetary policy shocks shift the price of invention, incentivizing the firm to invest more in intangible capital. Firms with low cash are financially constrained, while firms with high cash can freely choose the optimal level of investment. Overall, quantitative analysis indicates that the cash-in-advance constraint is an important force behind the heterogeneous innovation responses to expansionary monetary policy shocks.

Related Literature This paper contributes to several strands of the literature. First, this paper relates to the empirical literature studying the role of firms' heterogeneity in the transmission mechanism of monetary policy shocks. This includes recent papers by Cloyne et al. (2018); Jeenas (2019); Crouzet and Mehrotra (2020); Ottonello and Winberry (2020); Howes (2021) as well as earlier papers such as Gertler and Gilchrist (1994); Kashyap, Lamont, and Stein (1994). Substantial work has explored how heterogeneity across firms shapes the impulse response of tangible investment after a monetary policy shock. Such work has emphasized that a number of variables, such as size (Gertler and Gilchrist, 1994), age (Cloyne et al., 2018), liquidity (Jeenas, 2019), and leverage (Ottonello and Winberry, 2020), turn out to be the determinants of the dispersion in responses of tangible capitals. On the other hand, very few papers have explored the heterogeneous effect of conventional monetary policy on innovation, such as Morlacco and Zeke (2021); Döttling and Ratnovski (2021). However, the focus is still limited to intangible capital, such as "Selling, General and Administrative Expenses," which are unlikely to relate to productivity. To the extent that heterogeneity is important in understanding tangible capital responses after a shock, we cannot understand why TFP changes when there is an unexpected drop in interest rates without examining any heterogeneous responses in firms' innovation. In this regard, this paper is noteworthy because it is the first to understand the mechanism underlying the productivity effect of monetary policy shocks by looking at the dispersion in innovation responses depending on firms' cash holdings.

Second, this paper is part of the growing interest in the productivity effects of monetary policy. Prominent examples include Evans and dos Santos (2002); Christiano, Eichenbaum, and Evans (2005); Comin and Gertler (2006); Moran and Queralto (2018); Jordà, Singh, and Taylor (2020); Meier and Reinelt (2020); Garga and Singh (2021), where most work focuses on the effect of monetary policy shocks on productivity itself but not on the underlying mechanism. From the aggregate analysis, I also confirm the stylized fact that the expansionary shock increases the TFP. In this respect, this paper is still in line with previous works on aggregates. However, previous works mostly base their explanation on fixed costs (Christiano, Eichenbaum, and Evans, 2005), mark-up dispersion (Meier and Reinelt, 2020), and R & D (Moran and Queralto, 2018; Garga and Singh, 2021). This paper uses a novel measure of innovation in the field of monetary policy that is widely used in the literature on innovation. Through empirical analysis, this paper contributes to the literature by showing that the new measure of innovation can explain the productivity effect of monetary policy shocks and provides a new finding that the effect of monetary policy shocks on the valuation of innovation is large, which has only been discussed from the theoretical point of view. Moreover, the new measure in this paper is advantageous in that detailed firm-level data is also available, which enables me to explore what is underneath the productivity effect. While a few attempts have been made to explain what drives productivity effects in the short-run (Meier and Reinelt, 2020), none focus on what drives the productivity effect beyond the short-run. By exploring firm-level measures, I provide a novel explanation for TFP responses in the medium-run conditional on monetary policy shock.

Lay out The rest of the paper is organized as follows. Section 2 discusses the source of the data and how I construct each variable, including monetary policy shocks, financial variables, and innovation measures based on the patent applications. Section 3 and Section 4 presents the main findings. Section 5 provides a partial equilibrium model to explain empirical findings. Section 6 concludes.

2 Data

The aim of the present study is twofold. First, this paper is interested in estimating the effect of expansionary monetary shock on aggregate innovation, which is the primary driver of the productivity effect of the monetary policy shock. Second, this paper also emphasizes the role of liquidity in explaining the mechanism underlying the impact of the monetary policy shock on innovation. To answer these questions, I have merged three different sets of data. This section describes how a dataset is constructed.

Monetary policy shock To study the effect of monetary policy on innovation, it is essential to identify exogenous changes in monetary policy. This is because a time series of exogenous monetary policy shocks ensures that the findings in this paper are driven by an unexpected change in the monetary policy but not by other macroeconomic factors. The essence of identifying the monetary policy shock lies in distinguishing unanticipated and exogenous elements from current economic conditions. Following previous literature, I employ high-frequency methods to identify such exogenous changes in monetary policy.[6] Basically, the method uses the high-frequency movements in the Federal Funds futures on the current-month funds rate (FFR) in a small window period around the Federal Open Market Committee (FOMC) announcements to measure monetary shocks. The key assumption of this approach is that nothing but the press release can affect the Federal Funds Futures in a given window period around FOMC announcements. In this paper, I follow Gorodnichenko and Weber (2016) to construct the monetary policy shock ε_t^m as follows.

[6]Notable examples are Cook and Hahn (1989); Gürkaynak, Sack, and Swanson (2005); Gorodnichenko and Weber (2016).

$$\varepsilon_t^m = \frac{D}{D-t}(ffr_{t+\Delta^+} - ffr_{t-\Delta^-}) \tag{1}$$

where t is the time of the announcement, ffr_t denotes the federal funds futures rate, and Δ^+ and Δ^- are the times after and before the announcement, respectively. D is the number of days in the month, and t is the day of the meeting in the month so that $\frac{D}{D-t}$ makes adjustments for the timing of the announcement within the month. As a baseline analysis, Δ^+ and Δ^- are set to 45 minutes and 15 minutes, respectively, so that shocks are estimated based on the changes in the FFR within the 60-minute window around the announcement. The shock series starts in January 1990 because the federal funds rate market opened in 1990. The series ends in December 2007. This excludes the period after the great recession to avoid zero-lower bound issues and to focus only on conventional monetary policy. The resulting series needs to be aggregated because it is at the monthly level, while the firm-level data for the primary analysis is at the quarterly level. I aggregate the monthly high-frequency shocks to the quarterly frequency using the moving average method proposed in Ottonello and Winberry (2020), which weighs the raw shocks by the number of days in the quarter after the shock occurs to reflect the time firms have to respond to unexpected changes.

As a robustness check, I employ alternative methods to construct the monetary policy shocks. Specifically, I reconstruct the shock series with methods used in Gertler and Karadi (2015), Nakamura and Steinsson (2018), and Bauer and Swanson (2022).[7] Table 1 provides basic summary statistics of monetary policy shocks that are used in the final data sets.

Table 1: Summary statistics of monetary policy shock

	Gorodnichenko and Weber	Gertler and Karadi	Nakamura and Steinsson	Bauer and Swanson
Mean	-0.042	-0.044	0.000	0.000
Median	-0.005	-0.008	0.011	0.001
Standard deviation	0.124	0.110	0.065	0.069
Min	-0.479	-0.545	-0.267	-0.239
Max	0.261	0.170	0.145	0.195
Observations	72	72	77	128

Notes: Summary statistics of monetary policy shock starting. Shock series based on Gorodnichenko and Weber (2016) and Gertler and Karadi (2015) use the period from 1990Q1 to 2007Q4, Nakamura and Steinsson (2018) uses the period from 1995Q1 to 2014q1, and Bauer and Swanson (2022) uses the period from 1988q1 to 2019q4. The baseline shock measure in the paper is based on Gorodnichenko and Weber (2016).

In terms of baseline shock measures based on Gorodnichenko and Weber (2016), after aggregation, the shock series has 72 observations from 1990Q1 to 2007Q4. The median is around 0. One standard deviation of the quarterly shock is 12 basis points. The largest expansionary shock

[7] Bauer and Swanson (2022) argue that the shock series constructed based on the high-frequency method yields biased estimates of the effect of monetary policy shock on macroeconomic variables using local projections.

is 48 basis points, and the largest contractionary shock is 26 basis points. I attach the time series of the shocks in Figure (A.1) in Appendix A.

Balance sheet To construct firm-level data, I use the CRSP/Compustat Merged Database and the WorldScope Database at the Wharton Research Data service (WRDS). Both sources provide detailed balance sheet information for publicly listed U.S. incorporated firms covering the period from 1990Q1 to 2011Q4. Both databases contain recent information, but as I focus on firms' innovation, I limit the sample until 2011Q4 to use a piece of complete patent information. I will provide details on the construction of the patent dataset in the next part.

The benefit of using balance sheet data from WRDS is that it provides information on various firm characteristics at the quarterly level. The high-frequency feature is ideal for estimating the effect of monetary policy shock on firms' decisions. The detailed information on firms' financial status enables me to isolate the role of liquidity from other firm characteristics. In the main specification, I control all factors shown to determine tangible capital responses conditional on monetary shocks from previous literature to minimize errors due to confounding factors. These control variables include age, dividends, earnings before interest, taxes, depreciation, amortization (EBITDA), leverage, liquidity, long-term debt dependence, price-to-cost margin, net receivables to sales, real capital stock, real sales growth, size, and Tobin's q. Appendix B provides an overview of control variables and how they are constructed. Controlling for various firm characteristics allows me to accurately investigate the transmission mechanism of monetary policy on innovation by looking at which factors are the main drivers of heterogeneity in innovation responses conditional on monetary policy shocks. Every firm-level variable is winsorized at the 0.5% level to reduce the impact of outliers. The Appendix includes details on the construction of each firm-level variable. One limitation of using the balance sheet data from Compustat is that it only contains publicly listed U.S. firms, thus excluding private firms that are not listed on the stock market.

Patents I construct each firm's innovation measure using its patent application. The data is sourced from the U.S. Patent and Trademark Office (USPTO), which contains the history of U.S. patent documents. The advantage of using the dataset from USPTO is that the data is universal, which enables me to construct the innovation measure without any measurement error. However, one challenge is that the dataset has its own firm identifier, making it difficult to merge data with Compustat data. In this paper, I use crosswalk files from Bena et al. (2017) and Dorn et al. (2020) so that I can match the information as much as possible. As the stock variable is the usual way to handle investments in the literature, this paper's baseline measure of innovation is patent stocks. To be specific, with the given information, I construct the patent stock of each firm with a quarterly depreciation rate of 4%.[8] Additional measures are also considered in the robustness check, which

[8] Li and Hall (2020) document industry-specific R&D depreciation rates. However, the value is only available for major U.S.

I will discuss in Section 4. One limitation of the dataset from USPTO is that the information on patents granted before 1975 is relatively limited. Therefore, I supplement it with a constructed patent dataset from Kogan et al. (2017) because they include more information before 1975, thus enabling me to construct a rich dataset over the period.[9] One important takeaway from this paper is how the patent value responds to the expansionary monetary policy shock. In this regard, a dataset from Kogan et al. (2017) is also useful in gauging each patent's economic importance, as they construct the real value of each patent in dollar terms. To evaluate the economic value of each patent, they propose a new method that uses stock price reactions to patent grant news. The USPTO issues patents on Tuesday. In addition, it publishes the *Official Gazette*, which includes the list of newly granted patents and their detailed information, including technical descriptions. This news affects market participants because the market learns that the application was successful for the first time. Starting from Tuesday (i.e., the official announcement day of the Official Gazette), they estimate the change in total market capitalization until Thursday (3-day window period). After adjusting for aggregate market movements and idiosyncratic stock return volatility, the resulting series provides the economic value of innovation for shareholders. For illustration purposes, I summarized how they derive the value of the patents in Appendix B.

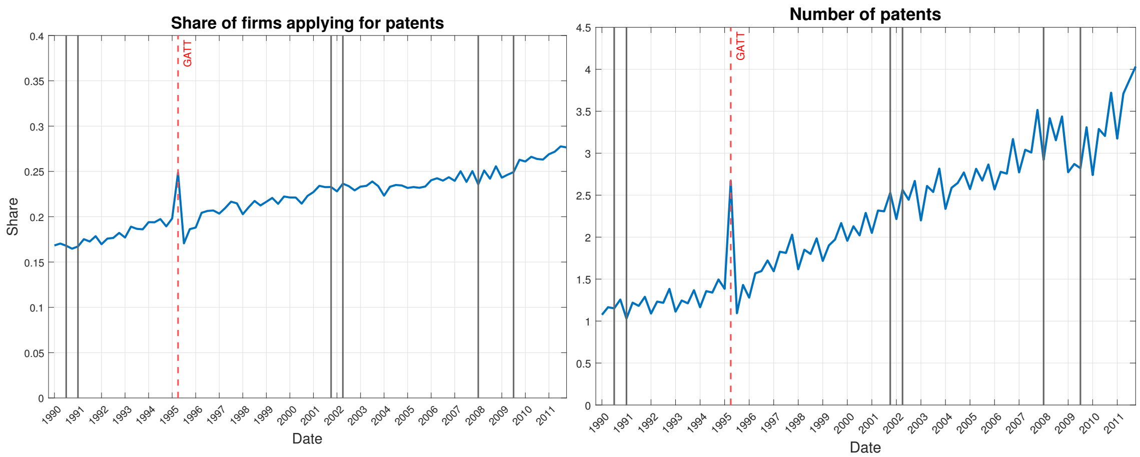
After constructing the innovation measure, I focus on the period 1995Q2 to 2011Q4 for the main analysis. In 1994, the U.S. president signed new law, the General Agreement on Tariffs and Trade (GATT). Starting in 1996, this legislation made significant changes to the U.S. patent law of which all users of the patent system should be aware. The legislation includes changing a patent's term of protection and establishing a domestic priority document designated as a provisional application. I construct the time series of aggregate innovation activities to see how this law affected firms' innovation activities. Figure 1 shows the results. The left panel shows how the proportion of firms applying for new patents changes over time. The right panel plots each firm's average number of patents conditional on having at least one patent in a given period. What is notable from these two figures is that there was a spike in the extensive and intensive margins of patent applications in 1995, the period right before the law became effective. Therefore, if I include the period before 1995, the effect of GATT will be captured by monetary policy shock, which will be problematic. To avoid any structural change arising from GATT, I drop the observations before 1995.

Furthermore, I limit the sample until 2011 to construct complete patent data set. In this paper, I assume that the patent application date and not the date when the patent was granted, is when the new technology was invented, as it is usually used to handle patent data in previous literature.

high-tech industries. In this paper, I follow the conventional setting and assume that the annual depreciation rate is 15%, which corresponds to 4% each quarter.

[9] As an alternative, I redid the analysis with the patent stock only with information after 1975Q1. I found no dramatic changes in the main findings of the paper.

Figure 1: Overview of aggregate patent applications



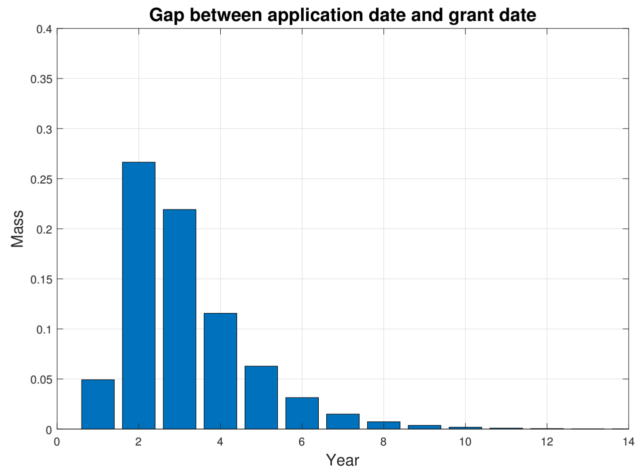
Notes: This figure plots the time series of overall patent applications from 1990Q1 to 2011Q4. The left panel shows the share of firms that filed patents in a given quarter. The right panel shows the average number of patent applications of firms.

However, patent data from USPTO only contains information on patents granted. This implies that the patents not granted yet are not included in the dataset, even if they were filed a while ago. Therefore, technology already invented but not patented is not reflected in the innovation measure in the paper by its construction. Therefore, using the whole dataset with no limitation will lead to inaccuracy in the innovation measure. It will get worse if it takes considerable time for new technology to get patented by USPTO. Figure 2 plots the histogram of the time gap between the application date of patents and their grant date. On average, it takes around three years for a patent to be granted after the application date, but sometimes it takes even longer. Roughly nine years correspond to 99% of the sample. This implies that most of the patents applied (i.e., invented) before 2011 should be included in the dataset published recently. Therefore, by limiting the sample until 2011, I can construct the complete firm-level innovation dataset.

One of the significant differences between this paper and the literature is how I construct firms' innovation measures. In this paper, firms' innovation variable is constructed using information about patent applications. Although one limitation of using patents as a measure of innovation is that not all inventions are patented, patents are still considered an important data source for the study of innovations because it is natural to think that inventions that change technology significantly should have been patented. However, not much attention was paid to the effect of monetary policy on productivity. Previous works focusing on innovations and monetary policy usually use R&D as a measure of innovation. Considering the purpose of this paper, there are good reasons why a firm's patent applications are an ideal measure for a firm's innovation compared to R&D.

First and foremost, patent data is relatively free from measurement issues that might prevent researchers from using firm-level R&D data. Compustat is notorious for inaccuracy in variables

Figure 2: Time gap between the patent application date and the date granted



Notes: This figure plots the histogram of the time gap between the date when firms file a patent application and the date when the patent is granted. Patent data is sourced from U.S. Patent and Trademark Office (USPTO). The sample period is from 1926 to 2021.

related to intangible capital. For example, in Compustat, using intangible capital(*intanq*) or R&D variable(*xrdq*) is problematic because they may not correctly reveal the firms' efforts regarding innovations. More than 70% of observations have a missing value for an R&D variable throughout the sample period. How to deal with missing values is crucial in this paper because the variation I am using in the main analysis is within-industry variation in the cross-section, which requires accurate measurements of innovation at the firm level. The conventional way to treat missing values is to consider them as 0 and assume it indicates a lack of innovation activity. However, no micro-founded evidence supports this rule-of-thumb method, and so it does not guarantee the accuracy of resulting innovation measures.[10] However, Koh and Reeb (2015) points out in their paper that the number of granted patents from firms with missing R&D is 14 times greater than those from firms with zero R&D. This suggests that a missing value for R&D does not always imply there is no effort in terms of innovations. Instead, due to its nature, which expense will be classified as R&D requires managers' discretion, and sometimes they choose not to disclose it separately in their financial statements. Second, patents are more likely to determine productivity growth than any other available measure. Firms' patent applications have been widely accepted as a proxy for "success" in creating knowledge capital. In addition, it has already been shown that there is a causality between a firm's productivity and patents. This confirms that what determines productivity should be the knowledge capital rather than the R&D, an input of innovations. Consequently, this paper overcomes the above mentioned challenges and provides reliable estimates using patent history data.

[10] Peters and Taylor (2017) provides helpful guidance to construct a comprehensive measure of intangible capital using Compustat. However, this method also sets R&D to zero when it is missing.

Final data set The final data set contains the financial variables discussed above and a stock of knowledge capital measured with patents at a quarterly frequency. Firm data is for the period from 1990Q1 to 2011Q4, while the monetary policy shock is from 1990Q1 to 2007Q4, before the financial crisis. Although I am focusing on the effect of conventional monetary policy shock on innovation, I extend the firm-level data until 2011Q4, thus enabling me to estimate the coefficient of interest over the longer horizon accurately. The final data set contains 253,227 firm-quarter observations. The sample only includes firms incorporated in the US and excludes firms in the financial industry or utilities.

Additional data I employ additional data to explore the transmission mechanism of monetary policy on innovation. Specifically, I use Mergent FISD and Dealscan to construct firms' borrowing in each period. I also use data from the Duke University/CFO Magazine Global Business Outlook survey of financial executives to explore how firms' financing decisions depend on changes in interest rates. A detailed description of data and the usage is available in Section 4.2

3 Aggregate Analysis

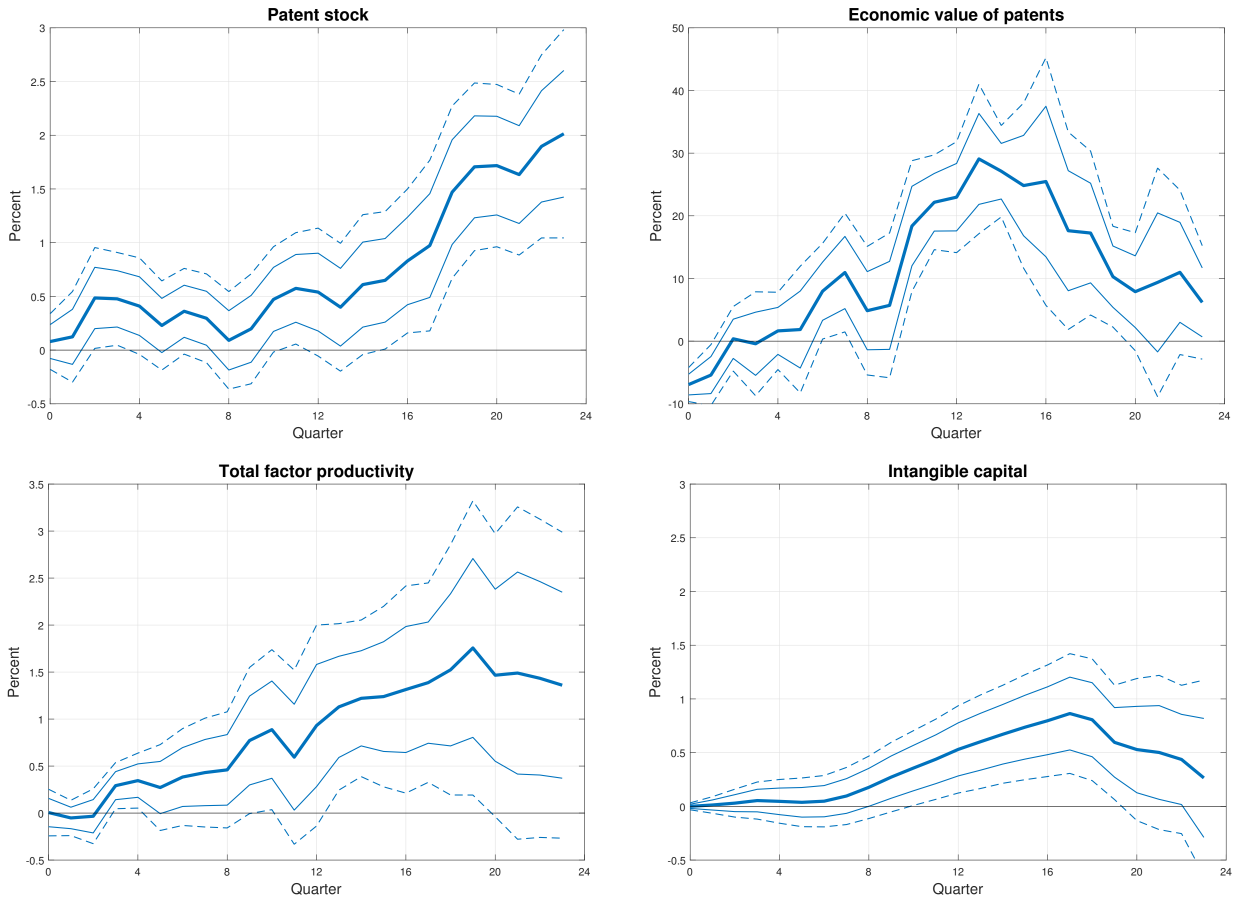
In this section, I conduct an aggregate analysis and emphasize the role of innovation in understanding the productivity effect of monetary policy shock beyond the short run. I provide evidence that the expansionary monetary policy shock increases the value of patents, aggregate patent applications, and TFP. From the evidence, innovation can be a channel through which monetary policy shock affects TFP.

Specification The main specification in this section is based on Jordà (2005) local projection. Specifically, I use the following specification from Coibion et al. (2017):

$$\log(y_{t+h}) - \log(y_{t-1}) = c^h + \sum_{j=1}^{J} \alpha_j^h \left(\log(y_{t-j}) - \log(y_{t-j-1})\right) + \sum_{i=0}^{I} \beta_i^h \varepsilon_{t-i}^m + X_t + u_{t+h}, \quad (2)$$

where $h \geq 0$ denotes the horizon; y_t is the variable of interest, and ε_t^m denotes the monetary policy shock as I discussed in Section 2. The coefficient of interest is β_i^h for $h = 0, \ldots, 24$, which measures the effect of monetary policy ε_t^m at period t on the growth rate of the dependent variable between $t-1$ and $t+h$. For the main analysis, I include six lags of the shocks (I = 6) and two lags of the quarterly aggregate innovation growth rate (J = 2). One issue with the specification is that ε_t^m might also capture any time-specific component. Therefore, I control for other aggregate variables, X_t, which include four lags of GDP growth, the inflation rate, and the unemployment rate to exclude such cases. Standard errors are computed using a Newey-west estimator with h lags. For each impulse response, I used a 68% and a 90% confidence interval. The sample period is from 1995Q2 to 2011Q4, with monetary policy shock available until 2007Q4. [11]

Figure 3: Impulse responses of aggregate variables to expansionary monetary policy shock



Notes: This figure plots the impulse responses of aggregates to a negative, one standard deviation monetary policy shock using the local projections method Jordà (2005). Quarterly TFP is from Fernald (2014), and monetary policy shock is constructed following Ottonello and Winberry (2020). For details, we use the exact specification as in Coibion et al. (2017). Standard errors are computed using a Newey-west estimator. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

Results The results are plotted in Figure 3. I make some adjustments to interpret the result easily. First, I multiply the dependent variable $(\log(y_{t+h}) - \log(y_{t-1}))$ by 100 so that I can interpret the dependent term as growth in the percentage point term. Second, I standardize and normalize the sign of the monetary policy shock ε_t^m, and hence, a positive value corresponds to an expansionary monetary policy shock.[12] The impulse response function in the figure shows how each macroeconomic variable responds to one standard deviation expansionary monetary policy shock.

[11] I conduct several robustness checks. First, I test if the result still holds after including the period before 1995Q1. Second, I extend the shock series until 2011Q4. Both cases yield a similar result to the main findings, which are in Appendix.

[12] One standard deviation monetary policy shock in this paper corresponds to a 13 basis point change in the federal funds rate.

To begin, let me revisit the arguments that monetary policy shock affects productivity growth over the longer horizon. For a measure of U.S. productivity, I use the quarterly, utilization-adjusted TFP series from Fernald (2014). The bottom left panel in Figure 3 shows the estimated impulse response of TFP based on specification (2). The aggregate TFP grows, and the effect persists beyond the short-run peaking 20 quarters after the shock. We can see the shock increases TFP approximately 1%, which is in line with the previous literature.[13]

To estimate how expansionary monetary shocks affect the innovation measured with patent applications, from the patent data I construct time-series data of the average number of patents that each firm holds in a given period. [14] The top left panel in Figure 3 plots the responses of aggregate patent stock. Patent stock increases slowly and peaks by around 6 years after one standard deviation expansionary monetary policy shock by 2%. One thing to note is that the initial response starts 4 years after the shock. This is reasonable because it takes time for an intangible investment to materialize, unlike tangible investments.

Moreover, the intangible investment also responds sluggishly to the shock, making aggregate innovation respond even later. To see how the shock shapes intangible investment responses, I use the data from the National Income and Product Accounts (NIPA) Tables of the U.S. Bureau of Economic Analysis (BEA). I only focus on R&D to construct firms' intangible capital stock. The impulse response function of the constructed variable is plotted in the bottom right. From the figure, we can see that intangible investments respond sluggishly to the expansionary monetary policy shock. After one standard deviation expansionary monetary policy shock, intangible capital increases by 0.8% at a 4-year horizon, but the response begins 2 years after the shock. This explains why R&D cannot explain the short-run fluctuations in TFP after the shock.

To supplement the argument, I plot the correlation between the patent application at time t and intangible capital at time $t-i$ where $i=-8,...,8$, which is in Figure A.12. The figure shows us that innovation at period t is correlated with the last eight quarters' investment, which explains why there is a time gap between when intangible capital starts to respond and when the patent stock shows the initial response. This paper is not the first to document intangible investments' sluggish response. Meier and Reinelt (2020) also found that R&D responds to monetary policy shocks sluggishly. What they focus on in their paper is the dispersion in the markup. Specifically, they provided such dispersion as a channel that can explain the short-run movement in productivity

[13] Meier and Reinelt (2020) reports a one standard deviation contractionary shock decreases the TFP by 0.5% 3 years after the shock.

[14] The sample used in the analysis consists of firms listed in Compustat data. When constructing the average number of patents in a given quarter, I assume that when the firm exits the market, the technology it owns also disappears. Therefore, I take an average of patents available in Compustat and exclude firms that exit in the same period. As an alternative, I also construct a different version of the series, which assumes that the patents keep depreciating even after firms exit the market. I also conduct the same analysis using entire patent data before merging it with the Compustat data. The result is in Appendix. Such changes do not make a dramatic difference in the main findings that an expansionary shock increases the aggregate innovation, which peaks around five years after the shock, except for confidence intervals on estimates.

after the monetary policy shock and argued that fluctuation in investment in R&D conditional on the shock could not affect the TFP in the short run. This paper is also interested in understanding the mechanism of the productivity effect of monetary policy shock. However, as I focus more on medium- long-run effects instead of short-run, I extend the horizon to 6 years to focus on medium-run productivity effects. In the Appendix, I plot how changes in patent stock affect TFP. Figure A.11 shows that the 1 percentage point change in patent stock leads to a 0.5 percentage point change in TFP in less than 1 year. This correlation suggests that the fluctuations in patent stock response can explain more than half of the fluctuations in TFP, emphasizing the role of patent stock in understanding the changes in TFP conditional on monetary policy shock. This suggests that aggregate innovation fluctuations can be the main driver of productivity growth conditional on monetary policy shock.

Is the estimate of the effect of monetary policy shock on innovation economically sizable? As a benchmark, I compare the estimated effect of monetary policy shock on innovation with the effect of the same shock on tangible capital in Figure A.13. Four years after one standard deviation expansionary monetary policy shock, tangible capital increases by 2%. However, long-run effects are imprecisely estimated with large standard errors. Furthermore, tangible investment shows instant responses after the shock compared to intangible investment. This suggests that the magnitude of the effect of the shock on innovation is economically significant, and it seems like the effect persists.

To rationalize such a significant and persistent effect on aggregate innovation, as evidence, I provide an appreciation of the value of patents after the shock, which incentivizes firms to invest in intangible capital. A conventional way of estimating the importance of a patent is by using citation-weighted patents, which reflect the scientific contribution of the new invention. However, one issue is that the scientific value of a patent may not correspond to the economic value of a patent because scientifically important innovations are sometimes the only ones that significantly impact firm profits. In terms of innovators, an increase in the patent's scientific value does not incentivize them to invest more in innovation because it does not guarantee their profits. Therefore, using the number of citations to estimate how monetary shock affects the valuation of a patent might not be relevant. In this paper, I address this hurdle by using the recently developed method of evaluating patents via market reactions to patent grant news by Kogan et al. (2017). Thus, I can construct the time series of the average economic value of a new patent granted in each period. Therefore, the constructed measure can be interpreted as what the market thinks of the total payoff of each patent at the time of the announcement, and this will be the firm's perception of the profitability of owning a new technology. This new methodology allows us to measure the average value of a firm's new patents each quarter and how this value responds to an expansionary monetary policy shock. The details about the construction of this variable are is in Appendix **??**. The value of new technology is the sum of the companies' future profits divided by the discount rate so that both the discount rate and profits determine the total value of the new invention. Expansionary monetary policy shock can affect these channels because it directly increases the discount rate and increases the profits through a cyclical upswing. From the top right panel, we can confirm that the expansionary monetary policy shock significantly increases the patent value. Three years after the shock, the estimated effect of the shock on the value of a patent is approximately 30%. The estimated effect of shocks on the patent value is larger than in the previous literature. Moran and Queralto (2018) shows that 60 basis points of expansionary monetary policy shocks can increase the value of new technology by 2% based on their theoretical model. Such a huge increase in the value of owning a new patent explains why expansionary monetary policy shock incentivizes firms to put more resources into intangible capital.

4 Firm-level Analysis

I next provide firm-level evidence to explore the mechanism underlying the effect of monetary policy shocks on firms' innovation. The section consists of two subsections. In the first subsection, I emphasize the role of firm characteristics in understanding heterogeneous innovation responses. In the second subsection, based on firms' borrowing and CFO survey data, I explore what drives the innovation heterogeneity conditional on monetary policy shock.

4.1 Heterogeneous innovation responses

In this subsection, the main goal of my analysis is to see which firms are the most responsive to the monetary shock. To do so, I show the differential effect of monetary policy shocks on firms' innovation depending on their characteristics.

Specification Aggregate evidence emphasizes the role of innovation in explaining the productivity effect of monetary policy shock. Based on these findings, I now explore which firms are the most responsive in innovation, which will clarify the underlying mechanism. To do so, I employ the local projection method proposed by Jordà (2005) to regress the cumulative difference of firms' innovation on the interaction terms of firms' characteristics determined in the period $t-1$ before the shock and monetary policy shock at time t.

The main measure of innovation is $\Delta \log(\text{Innovation}_{i,t})$, where $\text{Innovation}_{i,t}$ is the measure of innovation based on firms' patent applications. As a baseline innovation measure, I construct the stock of patents with a quarterly depreciation rate of 4% following Hall, Jaffe, and Trajtenberg (2005). Table 2 provides the summary statistics of the dependent variables used in the analysis.

Table 2: Summary statistics of firm-level variables

	$\Delta_1 \log(\text{Innovations}_{i,t})$	Count_{it}	$1(\text{Count}_{it} > 0)$	$1(\text{Count}_{i} > 0)$	Liquidity
Mean	0.017	3.46	0.267	0.681	0.159
Median	-0.006	0.00			0.073
Standard deviation	0.123	27.60			0.200
95th percentile	0.205	12.00			0.624
Observations		433091			

Notes: Summary statistics of firm-level variables computed over all firm-quarters observations starting from 1990Q1 to 2007Q4. $\Delta_1 \log(\text{Innovation}_{i,t})$ is the quarterly change in the patent stock of firm i at time t. Liquidity is cash and short-term investments to assets ratio. Liquidity is winsorized at a 99.9% cutoff.

Quarterly innovation growth exhibits significant variation, as with tangible capital growth cases. The median growth rate is around 0, and the average is approximately 2%. Moreover, a 12% of standard deviation suggests that the variable exhibits considerable variation in the cross-section. Liquidity shows significant variation as well. Furthermore, in each quarter, approximately 25% of all firms have at least one patent filed, and approximately 70% of firms have filed at least once throughout the sample period.

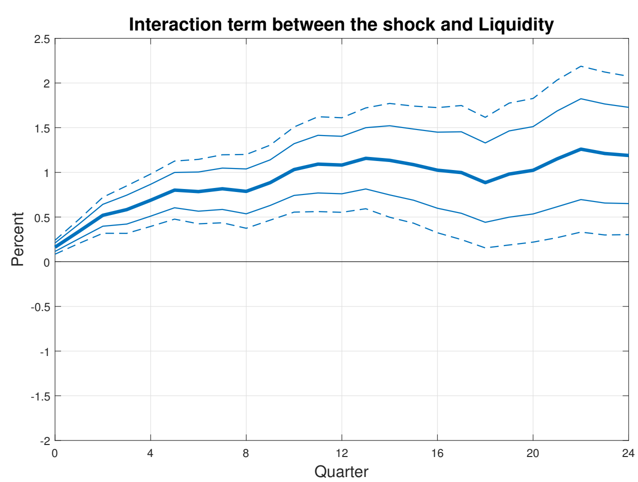
This is the first paper to estimate the semi-elasticity of innovation with respect to monetary policy shock depending on firms' financial position. Therefore, I include every firm control variable used in the previous works exploring the heterogeneous tangible capital investment responses to monetary policy shocks in the regression. To be as conservative, I include every interaction term of firm characteristics and monetary policy shock in the same estimating equation to ensure that omitted firm characteristics cannot explain the main findings. The baseline specification is as follows.

$$\Delta_h \log\left(\text{Innovation}_{i,t+h}\right) = \alpha_j + \alpha_{st} + \left(\Theta_h' + \varepsilon_t^m \Omega_h'\right) W_{jt-1} + u_{j,t+h}, \tag{3}$$

where $h = 0, 1, ..., 24$ denotes the quarters after the shock. The dependent variable, $\Delta_h \text{Innovation}_{j,t+h}$, is the h-period before cumulative growth of the innovation. α_j denotes the firm j fixed effect, which captures permanent differences across firms. $\alpha_{s,t}$ is a sector s by the quarter t fixed effect, and it captures the shocks that have an equal effect on the sector in a given quarter, so the results are not driven by industry differences. These sector-quarter dummies are constructed using the SIC 1-digit level. ε_t^m is the monetary policy shock, as discussed earlier. W_{jt-1} is in a vector of firm control variables. All the firm controls are measured at the end of the quarter before the monetary policy shock hits. This guarantees that firm characteristics used in the analysis are orthogonal to the shock. Last, $u_{j,t+h}$ is a residual. In the case of firm control variables, other than liquidity I also use a vast number of controls, including age, dividends, EBITDA, leverage, liquidity, price-to-cost margin, net receivables to sales, real capital stock, real sales growth, size, and Tobin's Q. These controls are the variables that have already been used as determinant factors in heterogeneous responses of tangible investment conditional on monetary policy shocks. Every firm-level variable is standardized, so its unit is the standard deviation of each variable. The main coefficient of interest is Ω_h, which is a vector formation. This term estimates how firms' innovation changes over time depending on their characteristics after monetary policy shocks. While it is common in the literature to look at the dynamic response of the variable of interest until 20 quarters after the shock, I estimate responses up to the horizon of H = 24 quarters. This is because, unlike tangible capital, intangible capital often shows sluggish responses to shock, as it is shown in Section 3. The standard errors are clustered two ways, by firms and quarters.

Results Figure 4 displays the results. To interpret the results easily, I make the same adjustments as in Section 3. Consequently, the positive value of an element in Ω_h is interpreted as firms with a higher level of corresponding firm characteristics will experience higher innovation growth after the one standard deviation expansionary shock. In this paper, I mostly focus on liquidity because liquidity overwhelms any other firm controls in magnitude and statistically. I also provide other estimates in Appendix, Figure A.2.

Figure 4: Dynamics of the differential response of innovation to monetary shocks

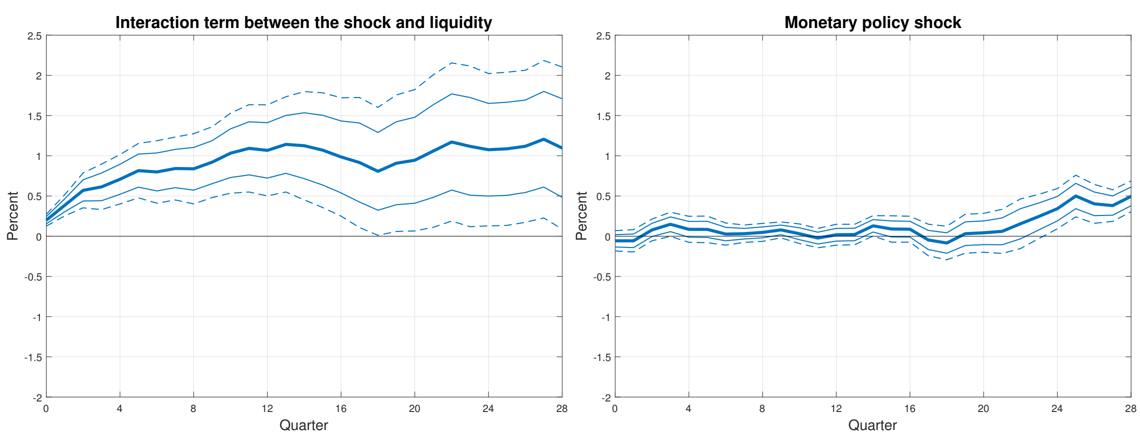


Notes: This figure plots the dynamics of the coefficient of the interaction term between liquidity and monetary policy shocks based on the specification (3). The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

As we can see, both in terms of magnitude and confidence interval, liquidity plays a large role in determining the dispersion in innovation responses after the shock. Specifically, after one standard deviation expansionary shock, one standard deviation more of liquidity leads to roughly one percentage point more innovation 3 years after the shock.[15] The peak of the differences in liquidity occurs after 5 years. However, the figure suggests that the effect does not disappear; instead, it persists even after that.

The point estimates in the figure are statistically significant. In order to gauge how important these numbers are, I calculate the 24-quarter growth rate of innovation with a given sample. Because the distribution of patent applications is highly skewed, the median growth rate is 0% and the mean growth rate is 25%. Therefore, the heterogeneity arising from the level of liquidity is not only statistically significant but also economically significant. Another way to check if this effect is economically significant is to compare the coefficient of an interaction term with the main effect as Ottonello and Winberry (2020) did in their paper. To do so, the effect of monetary policy shock on innovation should be estimated. However, the main specification cannot estimate such an effect due to the sector-by-time fixed effects. Therefore, I relax equation (3) and exclude sector-by-time fixed effects. Instead, I include a sector-by-seasonal-quarter effect and a vector of macroeconomic controls, including lagged GDP growth, the inflation rate, and the unemployment rate following Ottonello and Winberry (2020). Figure 5 shows the result.

Figure 5: Heterogenous impulse responses after expansionary shocks with average effect



Notes: This figure is based on specification 3 but excludes sector-by-time fixed effects α_{st}. Instead, I include ε_t^m and lagged GDP growth, inflation, and unemployment rates. The left panel plots the dynamics of the interaction term between firm control variables and monetary policy shock. The right panel plots the main effect of monetary policy shock, the coefficient on ε_t^m. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

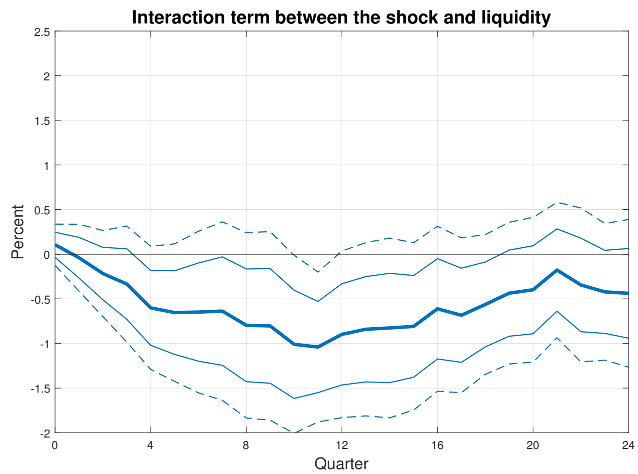
The coefficient of monetary policy shock can be interpreted as the effect of monetary policy shock on innovation in firms with zero cash holdings,which is close to 0. Adding the main effect does not significantly change the main findings. In addition, in terms of magnitude, the effect of

[15] I check if firms with high liquidity also experience higher productivity growth rates. Figure(A.14) shows the results. Firm-level productivity is sourced from İmrohoroğlu and Tüzel (2014). Because the firm-level employment data is only available at an annual frequency, firm-level TFP is also constructed at the annual level. This reduces the accuracy of estimates. However, overall, the productivity of high-liquidity firms grows more than those of low-liquidity firms.

the interaction term overwhelms the main effect. This again confirms that the coefficient of the interaction term is economically significant.

Another way to see how significant the effect of liquidity on intangible investment is conditional on monetary policy shock is to compare the coefficient to the results from previous works. As a benchmark, as it was in aggregate, I follow Jeenas (2019) and see how large the heterogeneous effect on tangible capital arising from liquidity is. The results are plotted in Figure(6).

Figure 6: Dynamics of the differential response of tangible capital to monetary shocks



Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on specification 3 but using tangible capital stock as a dependent variable. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

In the case of tangible capital, liquidity dampens the effect of monetary policy shock, which implies that after expansionary monetary policy shock, firms with high liquidity increase their tangible capital less than low liquidity firms, and the effect disappears with a longer horizon. As it is an aggregate analysis, the heterogeneous effect of monetary policy shock on innovation is as large as the effect on tangible capital, suggesting that the heterogeneity arising from the different levels of liquidity is economically sizable. One thing to note is that the sign of the coefficient is the opposite. Jeenas (2019) interpret the results as a contractionary shock, meaning that high-liquidity firms decrease their tangible investment after a contractionary monetary policy shock. However, this might not be contrary to the results of this paper. One way to address this is to split the monetary policy shock into contractionary shock and expansionary shock.[16] To be specific, I defined $\varepsilon_t^{m-} = \min(\varepsilon_t^m, 0)$ and $\varepsilon_t^{m+} = \max(\varepsilon_t^m, 0)$ and put them into specification (3) instead of ε_t^m to see if there is any asymmetry in the responses to the monetary policy shock. The results are shown in Figure A.9, which supports the asymmetric response of innovation to the sign of

[16] Wong (2018) split the monetary policy shock into expansionary shocks and contractionary shocks to estimate the effects of positive and negative shocks on household consumption separately.

monetary policy shocks. In this regard, the role of liquidity in this paper is not contrary to Jeenas (2019).[17]

Discussion and additional empirical results The main takeaway from the previous analysis is that there is a dispersion in innovation responses depending on firm characteristics. Furthermore, firms with high liquidity are the most responsive to shocks because they show more substantial innovation growth following an expansionary monetary policy shock. This leads to the conclusion that liquidity plays the most crucial role in explaining such heterogeneity. Moreover, one thing to note is how leverage matters. Whether or not firms are financially constrained is considered an essential factor in determining firms' investment decisions. (Ottonello and Winberry, 2020; Hori, 2020) In the main analysis, I also include leverage because leverage is usually used to proxy the level of such constraint. With the baseline measure, the estimated coefficient of the interaction term between the shock and the leverage is large and significant. However, the result was not robust to an alternative measure of innovation, particularly when the innovation measures are constructed based on their economic value, which causes the coefficients to be imprecisely estimated.

One issue with specification (3) is that the estimate cannot capture how the overall innovation response differs between firms with high-liquidity and firms with low-liquidity. To address this issue, I conduct additional analysis. I split the sample into two groups: high-liquidity firms and low-liquidity firms. High-liquidity firms are those with cash levels above the median at time $t-1$. The results are in line with the main analysis. The most response comes from the high-liquidity group than the low liquidity group. To be specific, I use the following specification for each group separately.

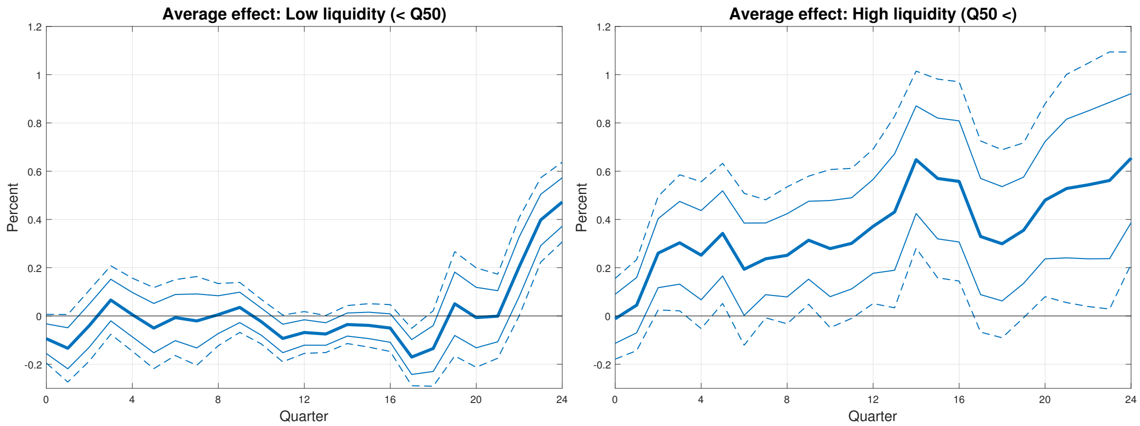
$$\Delta_h \log(\text{Innovations}_{i,t+h}) = \alpha_i + \beta_h \varepsilon_t^m + \Theta_h' W_{i,t-1} + u_{j,t+h}, \tag{4}$$

where $h = 0, 1, ..., 24$ denotes the quarters after the shock. The coefficient of interest is β_h. The coefficient captures the average effect of monetary policy shock on the growth rate of firms' measured innovation. Figure 7 plots the impulse response function of innovation to each group's expansionary monetary policy shock. As expected, the most response came from the high-liquidity group after the shock, while there was no response in the low-liquidity group.

Furthermore, I conduct a few robustness checks in Appendix A. The main findings are robust across a broad range of different assessment methods. The sample used for the main analysis covers the period 1995Q2 to 2011Q4. This is to exclude the period before the legislation changes. I

[17] One other possibility is that this might imply that the way liquidity works might be different for tangible capital. This is not surprising because tangible and intangible capital differ in several ways. One notable difference between them is how firms finance their investments. In the case of intangible investment, it is usually financed through internal funding because of a funding gap that arises from information asymmetry between the innovator and the debtor, as noted in Hall (2002). However, exploring the difference between these two is out of the scope of this paper.

Figure 7: Impulse response function of innovation to monetary shock



Notes: This figure plots the dynamics of the coefficient of monetary policy shocks based on specification (4) for two groups, high-liquidity and low-liquidity. Firms are divided into two groups depending on their level of liquidity in the period $t-1$. Those with liquidity above the median are defined as high-liquidity firms and the rest are defined as low-liquidity firms. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

consider including firm-quarter observation from 1990Q1 to 1995Q4, which yields results without any significant changes from the main estimates.

One potential problem of using the number of patents as a measure of innovation is that it does not capture the differences in the value of each patent. To address the issue, I use two alternative measures previously used in the literature. First, I use the number of citations each patent has up to 2021, which acts as a proxy for each patent's scientific importance.[18] I also use the economic value of each patent in dollar terms from Section 3 to measure the knowledge capital stock for each patent. The robustness checks with these alternative measures suggest that the main result using the number of patent applications holds.

The finding that innovation elasticities with respect to the expansionary monetary policy shock increase with the level of liquidity is also robust to different measures of monetary policy shock. I construct an alternative shock series based on Gertler and Karadi (2015) and Nakamura and Steinsson (2018). Both series yield a similar result. Lastly, I employ the shock series from Bauer and Swanson (2022). This reflects the ongoing debate over using high-frequency methods to construct monetary policy shock series. The basic idea is that monetary policy surprises are predictable before the FOMC announcement. This will violate the identifying assumption used in the high-frequency method that changes in the federal fund future in a short time window around FOMC announcements that arise due to news about monetary policy. As a result, estimates from local projections may be biased. Bauer and Swanson (2022) construct orthogonalized monetary policy shocks with respect to macro data to avoid such issues. Using orthogonalized shocks also does not

[18]Citation-weighted method is also widely used in the field of innovation. Examples include Hall, Jaffe, and Trajtenberg (2005); Aghion, Van Reenen, and Zingales (2013); Forman, Goldfarb, and Greenstein (2016).

yield any significant changes in the paper's main findings.

Last, although the R&D spending from Compustat is not very reliable, as I discussed earlier, I use the R&D expenditures of each firm and construct the intangible capital for each firm. One issue with making an intangible capital stock out of a series of R&D flow variables is missing information about the initial stock level. I overcome this problem by assuming the initial intangible stock in the first firm-quarter observation is equal to the R&D expenditures divided by the sum of the depreciation rate and 8% per year, which is a presample growth rate of new R&D following Hall (1990).

4.2 Mechanisms underlying heterogeneous responses

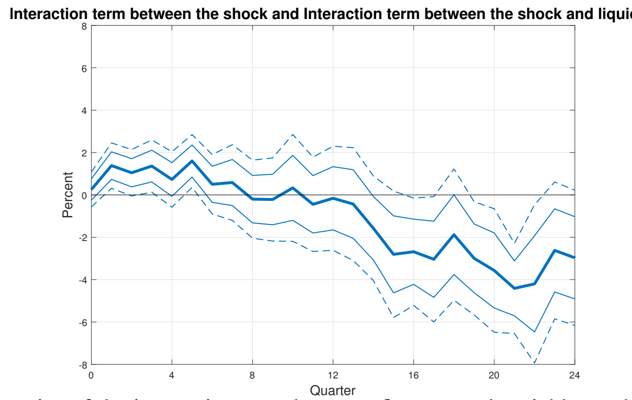
I next turn to the question of which force drives such heterogeneity in innovation responses. In this subsection, I provide some evidence to argue that financing innovations are the key to understanding the dispersion in reactions. Furthermore, I show that the reason why high-liquidity firms finance their intangible investment better is that those firms can easily access accumulated cash reserves to finance their investments.

Referring to Section 3 and Section 4, I show that expansionary monetary policy shocks increase aggregate innovation, and firms with high liquidity are the most responsive to the shock. The mechanism underlying the aggregate responses of innovations to monetary policy shocks is quite simple. Innovation does not guarantee profits at the time of invention; instead, it brings higher profits in the future. An unexpected decrease in the interest rate increases the value of patents, leading to an increase in aggregate innovation. However, which force drives the heterogeneity in responses is still unclear. Dispersion in responses can arise from heterogeneity in benefits or costs. For example, the patents of high-liquidity firms might be appreciated more than those of low-liquidity firms after the shock. However, the cost of financing the innovation is low for high-liquidity firms. Both cases will boost innovation more for firms with high liquidity than others. However, it is hard to tell which force drives the heterogeneity in firms' innovation decisions through estimated results in the previous section.

4.2.1 Heterogeneity in patent value

The focus in this subsection is not on the overall response of patent value to an expansionary shock but on the differential responses of the patent value depending on the liquidity level. The question is straightforward. Are patents of high-liquidity firms appreciated more after the shock? I use the value of patents from Kogan et al. (2017) to test this hypothesis. I use specification (3), but now the dependent variable is each firm's average value of new patents. There are some cases where firms patent more than one new technology in a given quarter t. I calculate the average value of new patents for each firm. After constructing the dependent variable, estimation is based on specification (3). However, I limit the sample only if a firm applies for at least one patent in both periods $t+h$ and $t+h-1$. This is because firms infrequently apply for a new patent, which makes x_t equal to 0 most of the time. Because I am focusing on how their valuation differs after the shock, excluding the firm-quarter observation without a patent application is reasonable.

Figure 8: Dynamics of the differential response of patent value to monetary shocks



Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3 but using patent value as a dependent variable. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

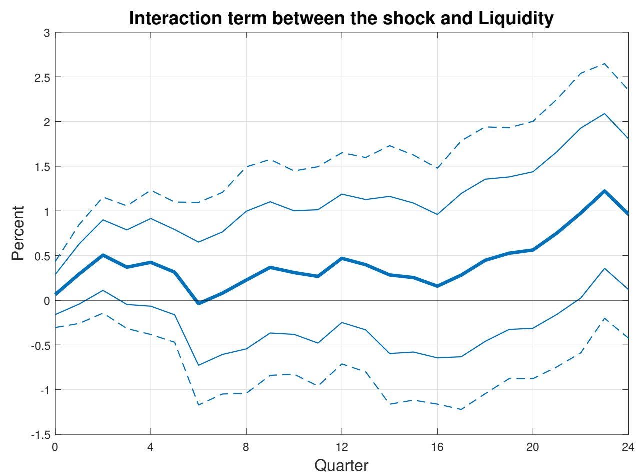
Figure 8 plots the dynamics of the interaction coefficient between firms' liquidity and monetary shocks over time. The figure shows that there is little evidence for heterogeneity in the valuation of patents–firms with low liquidity benefit from expansionary monetary policy shock in that their patent value appreciated more to the shock. This leads to the conclusion that the dispersion in innovation responses after the shock should arise from heterogeneity in financing.

4.2.2 Heterogeneity in financing

In this subsection, I provide evidence on how firms finance their innovative activities and show that this is the channel through which expansionary shocks determine the dispersion in innovation responses. What makes heterogeneity in financing? First, high-liquidity firms can use accumulated cash reserves, while low-liquidity firms have limited access to cash reserves. Second, there might be a decomposition issue whereby high-liquidity firms spend less on tangible capital and use it to finance intangible capital. Last, high-liquidity firms can borrow more. All three aspects can be candidates for the source of heterogeneity in financing. In this subsection, I will exclude the two latter cases and argue that the amount of cash in reserve is the source of heterogeneity in financing after the expansionary monetary policy shock.

Firms with high liquidity spend less on tangible capital One way for firms with high liquidity to innovate more than others after expansionary monetary policy shocks is to spend less on their tangible investment while financing intangible investments more. This can be easily tested by looking at how the ratio between intangible and tangible capital responds to the expansionary shock depending on the level of liquidity. To be specific, I use specification (3) but use changes in the ratio of intangible over tangible capital as a dependent variable. I follow previous literature focusing on tangible capital responses to construct tangible capital stock. (Ottonello and Winberry, 2020; Jeenas, 2019) Details are in Appendix B.

Figure 9: Dynamics of the differential response of the ratio between intangible and tangible capital to monetary shocks



Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on specification 3 but using the ratio between the patent stock and tangible capital stock as a dependent variable. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

Figure 9 plots the differential effect of expansionary monetary policy shocks on the ratio between intangible and tangible capital. Intangible capital is defined as patent stock in a given period t to be in line with the main analysis. The figure shows no heterogeneous effect of monetary policy shock on the ratio until 4 years after the shock. Still, there is little support for high-liquidity firms investing more in R&D compared to tangible capital. However, this difference cannot be a source of heterogeneity in innovation. As has been emphasized before, the notable difference between intangible and tangible capital is that it takes a certain amount of time for an intangible investment to materialize, around 2 years from the correlation between the patent applications and intangible capital. This implies that the response occurring 5 years after the shock, as in the figure, cannot explain such heterogeneity in innovation responses. The conclusion is therefore that the heterogeneous innovation responses arise from other factors.

Firms with high liquidity borrow more Does heterogeneity in innovation then arise from heterogeneity in borrowing decisions of firms after the shock? Here, I would like to revisit what we know about borrowings for intangible investment from previous literature. Previous literature points out that investment in innovations differs from tangible capital in several aspects. Two notable characteristics that distinguish intangible from tangible investment are information asymmetry between innovator and debtor and lack of collateral value. Often, these features are cited as a reason why firms usually depend on internal financing when it comes to R&D. Because of the "funding gap" for R&D, firms prefer using cash on hand to finance their investments rather than relying on outside financial intermediaries.[19] Moreover, the low collateral value of intangible capital also leads to insufficient lending.[20]

This stylized fact is also confirmed by the dataset used in this paper. I divide firms into 50 groups depending on their patents' stock and take each group's average liquidity. The stock of patents is divided by the size of firms for normalization to ensure that the result is not driven by the fact that large firms tend to have more patents and cash. Figure 10 plots the distribution of each bin and fitted line. The first column uses patent stock, and the second column uses the growth rate of patent stock as a measurement for innovation. The top two panels show the correlation between liquidity and innovation. A positive correlation between the stock of innovations and liquidity implies that firms rely on more cash as they are more innovative. The result is robust when using growth in the stock of patents instead of the level of innovation measures. However, if I use leverage instead of liquidity, the figures look different. The bottom two panels show that innovative firms tend to deleverage.[21] The result reconfirms that the cost of financing the R&D is high, so it is unlikely that firms will rely on leverage to fund their R&D. Consequently, it is less likely for borrowing to explain any fluctuation in intangible investment after the shock.

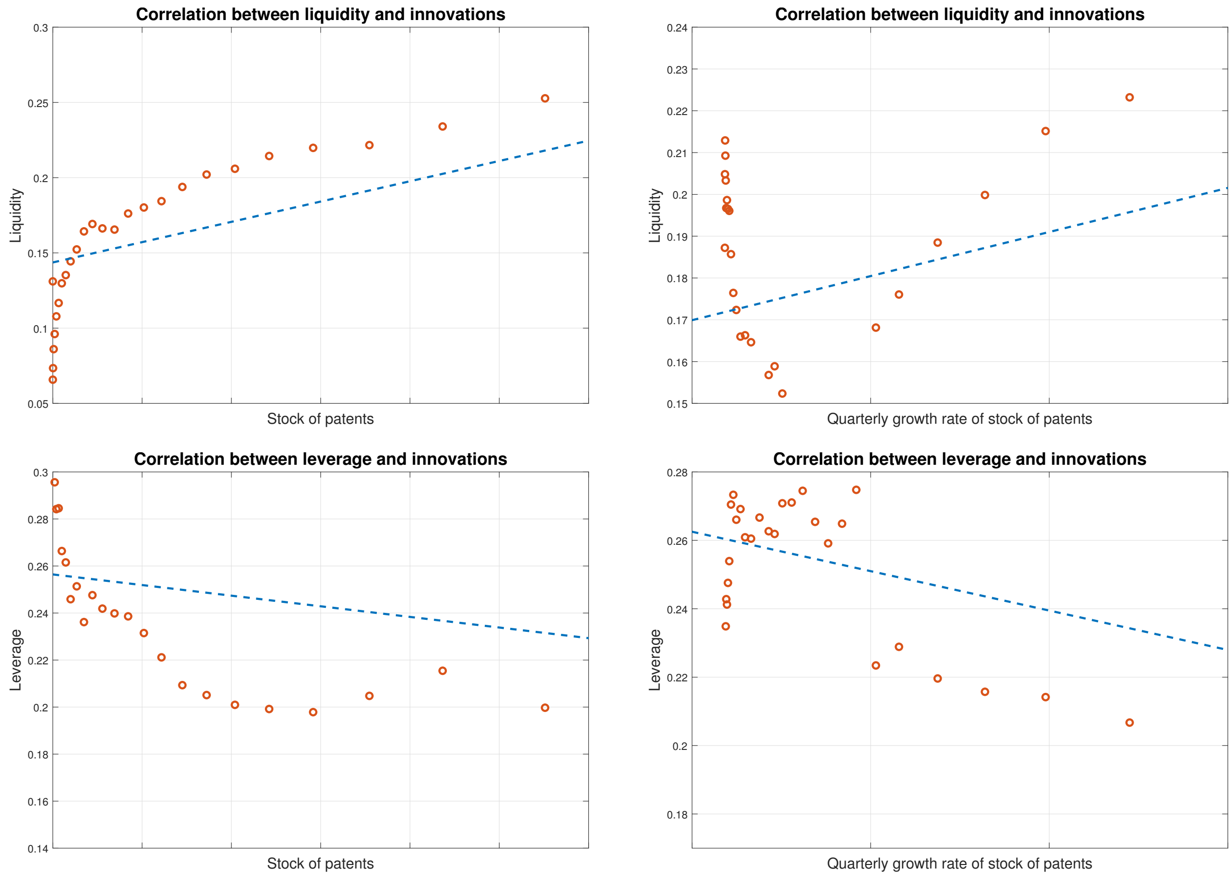
However, this paper focuses on how firms' decisions change after monetary policy shocks. Consequently, how firms' marginal financing decision changes after the shock is more relevant. After unexpected circumstances, firms have two options to finance their investments. One is their cash on hand, and the other is leverage. In the case of tangible capital, the borrowing channel plays a vital role in understanding the heterogeneous responses depending on firms' characteristics, as it is already emphasized in previous literature, such as Ottonello and Winberry (2020). In this paper, I will provide conditional evidence using borrowing and CFO survey data to check if the analogous still applies to intangible capital.

[19] See Hall (2002); Brown and Petersen (2011)

[20] Falato et al. (2020) studies how increasing intangible capital relates to a secular upward trend in U.S. corporate cash holdings. In their mechanism, the low collateral value of intangible capital plays an important role.

[21] Figure A.18 plots the correlation between firms' equity financing and innovation. The result suggests that firms rely more on equity financing as they become more innovative.

Figure 10: Correlation between (liquidity/leverage) and innovations

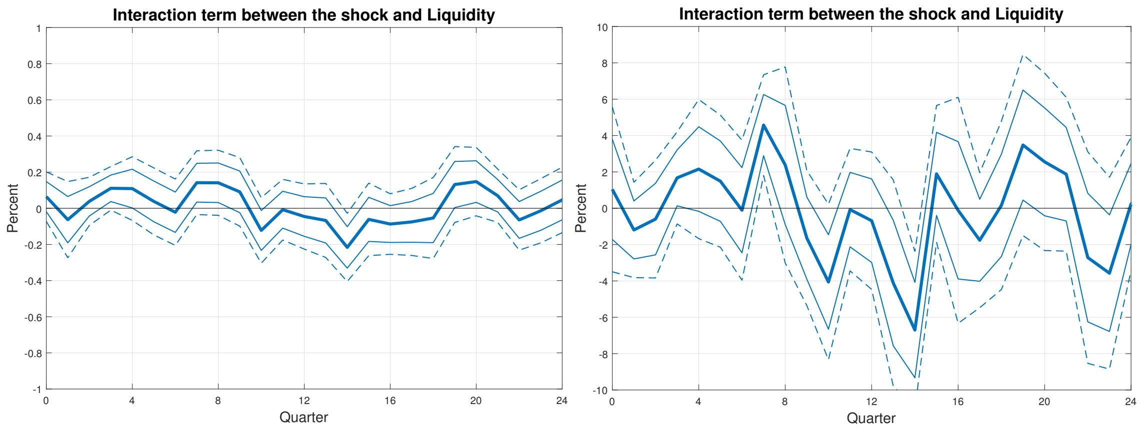


Notes: This figure plots the correlation between firm characteristics and innovation using the binned scatter with a fitted line. The top two panels show the correlation between liquidity and innovation, and the bottom two panels show the correlation between leverage and innovation. The left panel use patent stock divided by firms' total assets for normalization, and the right panels use the growth rate of patent stock as a measure of innovation.

As a first step, I use firms' borrowing data and see how these change after the shock. I use both bonds data from Mergent FISD and loans data from Dealscan. I use specification 3, the exact specification that was used in the main analysis, instead of using innovation measures as a dependent variable. I use a dummy variable, $1(\text{New Issue})$, which gives a value of 1 if firms issue any new type of borrowing in the given quarter t and 0 if not. I also construct the outstanding borrowing amount of each firm. Under this setting, Ω_h' from specification 3 now captures whether liquidity increases the probability of issuing new loans or the total borrowing amount after the expansionary monetary policy shock.

Figure 11 presents the results. The left panel plots the results with the probability of issuing new types of borrowings as a dependent variable, while the right panel plots the impulse response of total borrowing amounts. No matter which dependent variables are used, there is no heterogeneity in firms' borrowing activities depending on the liquidity levels, which leads to the conclusion that

Figure 11: Dynamics of the differential response of borrowings to monetary shocks



Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on specification 3. The left panel uses the probability of issuing new borrowings, while the right panel uses the total amount of borrowing as a dependent variable. The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

the firms' borrowing decisions are not affected by liquidity levels.

I also provide additional evidence based on the survey data from the Duke University/CFO Magazine Global Business Outlook survey of financial executives. In September 2012, the survey added a question asking participants how much their borrowing costs would have to decrease to cause them to accelerate investment projects in the upcoming year. Sharpe and Suarez (2021) use the data and find that the borrowing cost sensitivity is low. I modified their methods slightly and checked the borrowing cost sensitivity of firms with expected growth in R&D controlled. The specification is as below.

$$
\begin{aligned}
&\text{Prob(No reaction to decrease = 1)}_j \\
&= \alpha_{\text{ind}} + \beta_1 \text{Expected R\&D Growth}_j + \beta_2 \text{Working capital concerns}_j \\
&+ \beta_3 \text{Expected R\&D Growth} \cdot \text{Working capital concerns}_j \\
&+ \beta_4 \text{Expected Capital Growth}_j + \beta_5 \text{No plans to borrow}_j + \beta_6 \text{Balance sheet concerns}_j \\
&+ \beta_7 \text{Size}_j + \beta_8 \text{Private}_j + u_j
\end{aligned} \tag{5}
$$

For a dependent variable, I construct a dummy variable $\text{Prob(No reaction to decrease = 1)}_j$, which gives a value of 1 if firms answer that no rate change would affect their investment plans.[22] The dependent variable measures how insensitive firms' borrowings are to interest changes. Working capital conce and Balance sheet concerns_j are dummy variables that indicate if a firm indicated working capital management or the balance sheet are among its top three concerns. No plans to borrow_j and Private_j are dummy variables that determine if a firm has no plans to borrow and if it is owned by

[22]The most commonly cited answer to this open-ended question is that firms have ample cash reserves.

Table 3: Probability of No Reaction to Interest Rate Decrease

Dependent variable	No reaction to decrease		
	(1)	(2)	(3)
Expected R&D Growth	0.007	0.012**	0.010*
	(0.005)	(0.006)	(0.006)
Working capital concerns	-0.193**	-0.161**	-0.232**
	(0.074)	(0.082)	(0.086)
Expected R&D Growth x Working capital concerns	0.001	-0.006	-0.002
	(0.105)	(0.012)	(0.013)
Expected Capital Growth	-0.000	0.000	0.000
	(0.015)	(0.012)	(0.018)
No plans to borrow	-0.085	-0.029	-0.075
	(0.059)	(0.064)	(0.068)
Balance sheet concerns	-0.013	0.042	0.010
	(0.080)	(0.088)	(0.090)
Uncertainty concerns	0.086	0.191**	0.132**
	(0.061)	(0.067)	(0.069)
Size	-0.022	-0.036*	-0.035
	(0.019)	(0.021)	(0.022)
Private	0.071	0.097	0.110
	(0.072)	(0.079)	(0.084)
Observations	234	234	192

Notes: Results from estimating specification(5). Prob(No reaction to decrease = 1)$_j$ is a dummy variable that gives a value of 1 if firms answer that no rate change would affect their investment plans. Working capital concerns$_j$ and Balance sheet concerns$_j$ are dummy variables that give one if a firm indicated working capital management or the balance sheet among its top three concerns. No plans to borrow$_j$ and Private$_j$ are dummy variables that give one if a firm has no plans to borrow and if it is owned by a private, respectively.

a private, respectively.

Table 3 reports the results from estimating specification (5). I use three ways to construct the dependent variable, each corresponding to each column respectively. First, I use the dependent variable without any adjustment. Second, I assume that those who report they do not respond to changes in borrowing costs because the interest is already low are not insensitive to changes. Last, I drop the observation if they correspond to the former case. Based on the first definition, the dependent variable might not be relevant because this paper aims to see how firms respond to unexpected changes in the interest rate rather than how their innovation changes when there is a long-term low-interest rate. Table 3 shows the results. If firms expect their R&D spending to grow in the next 12 months, they become insensitive to changes in borrowing costs. Depending on the definition, if their expectation grows by one percentage point, then the probability of being insensitive grows by around 1.0 percentage points. The estimate based on the sample without any adjustment is not statically significant, while the other two provide significant results. This is in line with the unconditional evidence I provided earlier. Because it is usually hard to finance intangible investments with borrowings, firms finance them internally. This implies that changes in borrowing costs would not affect firms' borrowing decisions, as they already plan to finance with a cash reserve. Jeenas (2019) uses the independent variable Working capital concerns to proxy the liquidity level of each firm, implying that firms with working capital management concerns lack liquidity. In this paper, I also assume that working capital concerns imply firms have a low level of liquidity. In the first column of Table 3, we can see that as firms indicate working capital as their major concern, they are sensitive to borrowing cost changes. Although the magnitude depends on the definition of the dependent variable, overall, the estimate is large: if a firm has a working capital concern, then the probability of the firm being insensitive drops by 16 to 25 percentage points. This is reasonable because those lacking cash reserves should rely on borrowings from outside intermediaries to finance their investments. The goal of this section is to show that there is no heterogeneity in borrowing depending on the level of liquidity. To do so, I construct an interaction term of expected R&D growth and working capital concern so that β_3 captures any heterogeneity in borrowings arising from different cash levels. The results are in the second column. The coefficient itself indicates that those with less cash, holding the expected R&D growth rate constant, are sensitive to changes in borrowing costs, which is broadly in line with what β_2 captures. However, the effect is not statistically significant, implying that heterogeneity in financing cannot be explained by heterogeneity in borrowing depending on firms' liquidity level.

The results in this section suggest that the underlying reason for heterogeneous innovation responses after an expansionary monetary policy shock is heterogeneity in financing than the valuation of patents. Furthermore, the heterogeneity in financing arises because firms with high liquidity can easily access their accumulated cash reserves to finance their new intangible investments.

5 Theoretical framework

This section describes the partial equilibrium to understand how innovators generally manage their cash holdings and how their financing decisions change monetary policy shocks. The model's skeleton is from the Romer-style growth model, meaning that the number of products innovators produce measures productivity. Over the last few decades, a fundamental transformation from a tangible-reliant economy to an intangible-reliant economy has occurred, which has attracted the interest of many researchers.[23] However, because of features of intangible capital that distinguish

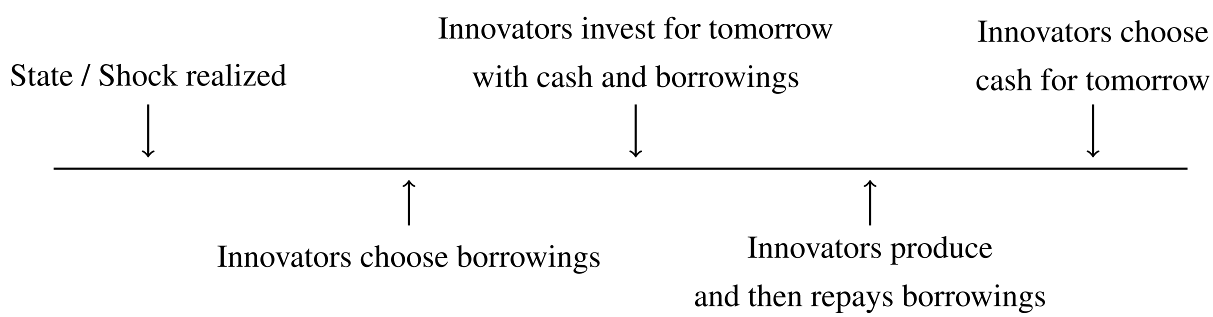
[23]Investments in intangible capital have risen significantly. In particular, the share of intangible investments from GDP has grown from 1% to 6%, while the share of tangible investments is relatively constant throughout the period. See Figure A.19.

it from tangible capital, previous works found that additional constraint is necessary for the model. In this section, I will integrate those constraints into the model and show that firms with high liquidity benefit disproportionately from an unexpected decrease in monetary policy.

5.1 Environment

5.1.1 Timing

In this paper, innovators' decisions are simultaneously made. For the purpose of the narrative, the timing of the decision is as follows.



After information on the shock and the aggregate state is revealed, innovators choose intra-period borrowing at the beginning of the period. Then, innovators hire new researchers and build intangible capital using reserved cash or borrowings. I assume the innovator uses a linear production function to build intangible capital using labor, so hiring is equal to the investment in the model. After choosing the optimal level of investment, innovators produce with a given amount of intangible capital, repay the borrowings at the interest rate, and choose a cash for tomorrow.

5.1.2 Technology and Production

Innovators use intangible capital (S_t) for production. Specifically, with S_t, innovators can produce $z_t \cdot (S_t)^{\alpha}$ amount of new designs where each of them is selling for price p in the market. In particular, the operating income of the innovators is given by:

$$\Pi_t = p \cdot z_t \cdot (S_t)^{\alpha}, \tag{6}$$

where α captures the degree of decreasing returns to scale and z_t is an idiosyncratic productivity shock that follows AR(1) process $\log z_{it+1} = \rho \log z_{it} + \varepsilon_{it+1}$, where $\varepsilon_{it+1} \sim N\left(0, \sigma^2\right)$.

Each innovator hires new researchers at the wage w to build up intangible capital stock. In particular, innovators have the same production function to produce intangible investment, which is a linear function ($n_t = i_t$). Because it is linear, we can use i_t instead of n_t. I assume that firms' intangible capital follows the law of motion:

$$S_{t+1} = (1-\delta)S_t + i_t, \tag{7}$$

in which δ is the depreciation rate. Following Cooper and Haltiwanger (2006); Belo et al. (2017), I assume the new investment is accompanied by adjustment cost, which is described below.[24]

$$AC(i_t, S_t) = \begin{cases} F^i S_t + \frac{c^i}{2}\left(\frac{S_{t+1}-(1-\delta)S_t}{S_t}\right)^2 S_t, & \text{if } S_{t+1} \neq (1-\delta)S_t \\ 0, & \text{else} \end{cases} \tag{8}$$

One crucial feature of intangible capital is that it is irreversible, which can be explained by the fact that intangible capital embodies the human capital of researchers. While physical capital is tradable among economic agents, human capital cannot be easily transferred to others. To model this, in this paper I assume that innovators hire researchers and transform labor into intangible capital. Because innovators cannot employ a negative amount of labor ($n_t \geq 0$), the assumption that intangible capital is irreversible is already embedded in the model. We can also think of it as innovators cannot sell their accumulated intangible capital as well ($i_t \geq 0$).[25]

5.1.3 Financing

In this model, innovators rely on two sources of financing when they hire new researchers, borrowings and cash reserves. Evidence from Section 4 suggests that innovators rely on cash on hand to support their intangible investment for both regular and unexpected periods with monetary policy shocks. In this subsection, I provide some additional features of borrowings for intangible investment and discuss the constraints embedded in the model.

Borrowing I denote firms' intra-period debt contract by L_t. Here, I would document two important features of intangible assets, such as a patent. First, it is a well-known fact that intangible assets support less debt than tangible assets.[26] What distinguishes intangible capital from tangible capital is that tangible capital is usually in physical form. However, intangible capital is usually referred to as invisible assets. These resources do not have a physical, or sometimes even a paper, presence. Hence, in terms of the debtor, intangible capital is difficult to verify in quality or quantity. Consequently, intangible capital is rarely pledged as collateral in debt contracts. Based

[24] Belo et al. (2017); Moran and Queralto (2018) introduce convex adjustment cost of R&D. Belo et al. (2017) document that the adjustment cost of hiring high-skilled labor is high. As conventional wisdom assumes that the high-skilled worker usually produces intangible capital, the costs can also be considered as adjustment costs for R&D.

[25] See Weiss (2019), Falato et al. (2020).

[26] See Rampini and Viswanathan (2010) for theoretical arguments, and Sibilkov (2009) for empirical evidence.

on the micro-foundation, previous literature often assumes that only tangible capital can be used as collateral. However, Mann (2018) points out that firms can use the patent as collateral, which helps U.S. firms raise significant debt financing.[27] To capture both features, I assume that firms' intra-period debt contracts can be written on the outcome of the firms' output today. The resulting contract for risk-free debt is subject to the following borrowing constraint:

$$L_t \leq \theta \cdot p \cdot z_t \cdot (S_t)^{\alpha}, \tag{9}$$

Note that the collateral value also depends on the realization of the shock at the beginning of the period. Moreover, I assume that firms must pay underwriting fees to tap into the credit market. Altınkılıç and Hansen (2000) found that bond issuance is accompanied by extra cost, which increases as the amount of issuance increases. In particular, the issuer's spread is a U-shaped function of the amount of new borrowings. To align with their empirical finding, I introduce the underwriting fee $UC(L_t)$, a function of the borrowing amount.

$$UC(L_t) = \begin{cases} F^L + c^L L_t^2, & \text{if } L_t > 0 \\ 0, & \text{if } L_t = 0 \end{cases} \tag{10}$$

Internal funds A firm can accumulate cash reserve (B_t) in the model. This paper is an abstract of equity financing. Instead, I embedded dividend non-negativity constraint, enabling me to reflect on the stylized facts regarding equity financing in the literature. A large body of empirical research provides evidence regarding the issuance costs of equity financing.[28] Furthermore, firms issue equity very infrequently. Consequently, previous works often rely on dividend non-negativity constraints to reduce the computation burden and reflect features of equity financing simultaneously. Such constraint makes borrowing from an outside intermediary costly. Firms hold cash on hand to avoid such high costs, which yields no interest for investment tomorrow.

Financing intangible investment From Section 4, I provide unconditional evidence that innovative firms rely more on cash and less on leverage, which is in line with previous works emphasizing the role of liquidity in intangible assets. The "funding gap" is a well-known fact about borrowings for intangible investment, implying that external financing for R&D investments might be more costly than other types of investments.[29] Moreover, it is well documented in the literature that firms tend to rely on cash to finance R&D (Berentsen, Breu, and Shi (2012); Chu, Cozzi, and Galli

[27] Falato et al. (2020) uses a large sample of syndicated loans and verifies that contractual loan terms state that only assets that can be easily valued represent eligible collateral. They also report that only a small minority of loans have patents as collateral.

[28] Notable examples are Altınkılıç and Hansen (2000); Bolton, Chen, and Wang (2011). Specifically, Bolton, Chen, and Wang (2011) argues that fixed equity issuance costs strengthen firms' precautionary demand for cash.

[29] For example, empirical studies such as Brown, Fazzari, and Petersen (2009) provide evidence that financial constraints matter for R&D investments more than for other types of investments.

(2014); Hori (2020)). Following these authors, I introduce a cash-in-advance (CIA) constraint in the innovators' problem. In the model, innovators have two sources of financing: internal funds and debt. Therefore, they face one additional constraint, $B_t + L_t - UC(L_t) \geq w_t \cdot i_t$. This implies that innovators can only hire new labor with less than cash on hand plus borrowing, which is described below. Each firm maximizes the dividend payout to shareholders (D_t). In each period, the innovator maximizes the following.

$$\max_{\{i_{t+j}, B_{t+1+j}, L_{t+j}\}_{j=0}^{\infty}} \mathbb{E}_t \sum_{j=0}^{\infty} \left(\frac{1}{1+r}\right)^j \cdot \Pi_{t+j} \tag{11}$$

$$\Pi_t = p \cdot z_t \cdot (S_t)^{\alpha} + B_t - B_{t+1} + L_t - (1+r) \cdot L_t - UC(L_t) - w \cdot i_t - AC(i_t, S_t)$$

$$i_t = S_{t+1} - (1-\delta) \cdot S_t$$

5.2 Value maximization problem

To estimate the effect of monetary policy shock, I define three aggregate states of the economy in the model—low interest rates, middling interest rates, and high interest. Each state determines the real price of an invention, real interest rate, and real wage, and I assume that there is one standard deviation of monetary policy shock between each state. Based on the empirical findings, unexpected changes in the interest rate changes the price of an invention, real wages, and the real interest rate accordingly. In this setting, expansionary monetary policy shock shifts the merit of invention, incentivizing the firm to invest more in intangible capital. Firms with low cash are financially constrained, while firms with high cash can freely choose the optimal level of investment. The innovator problem can be defined in recursive form as follows.

$$V(S, L, z, M) = \max_{i, B', L} \left(D(M) + \frac{1}{1+r(M)} \mathbb{E}[V(S', B', z', M') \mid z, M] \right) \tag{12}$$

$$D(M) = p(M) \cdot z \cdot S^{\alpha} + B - B' + L - (1+r(M)) \cdot L - UC(L) - w(M) - AC(i, S)$$

$$i = S' - (1-\delta) \cdot S$$

$$B + L - UC(L) \geq w(M) \cdot i$$

$$i \geq 0$$

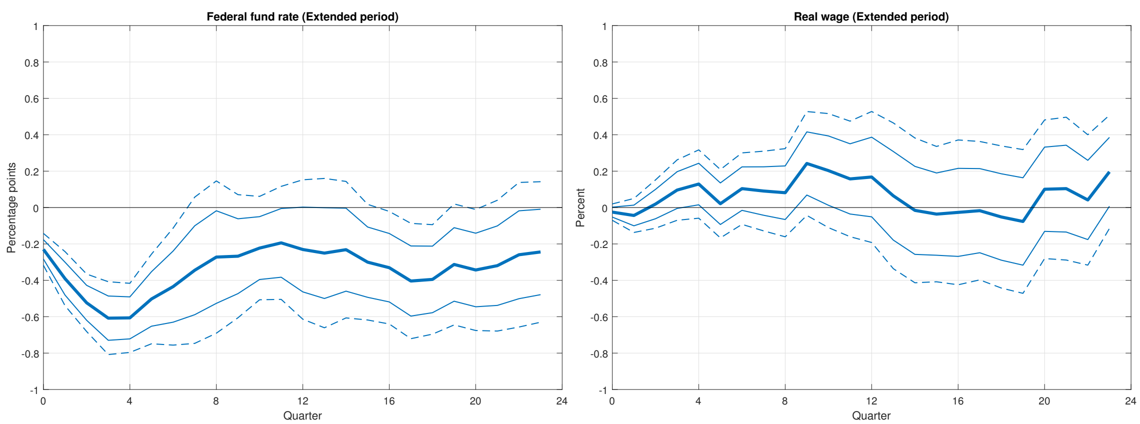
$$\theta \cdot p(M) \cdot z \cdot S^{\alpha} \geq L$$

$$D(M) \geq 0$$

5.3 Impulse responses and Discussion

This subsection aims to replicate the differential effect of expansionary monetary policy shocks on firms' innovation. It is important to note that the transmission of monetary policy shocks to innovation arises from a large increase in patent value, as I show that an unexpected decrease in the interest rate affects the price of new patents, which drives the firms' innovation responses after the shock in Section 3. Moreover, patent value is not the only thing affected by monetary policy. An unexpected decrease in the interest rate determines the real interest rate and the real wage. This in turn implies that it is essential to embed these features into the model to estimate any effect of monetary policy on innovation. Then, how does monetary policy shock shapes the real interest rate and real wage in the data? The answer will guide the proper magnitude of shocks in the model. To this end, I use the U.S. effective federal funds rate and real wage from the Federal Reserve Economic Data (FRED) database and follow specification (2).

Figure 12: Impulse responses of the real interest rate to expansionary monetary policy shock



Notes: This figure plots the impulse responses of real interest rate and real wage to a negative, one standard deviation monetary policy shock using specification (2). The solid line indicates the one standard deviation, and the dotted line indicates the 1.65 standard deviation confidence interval.

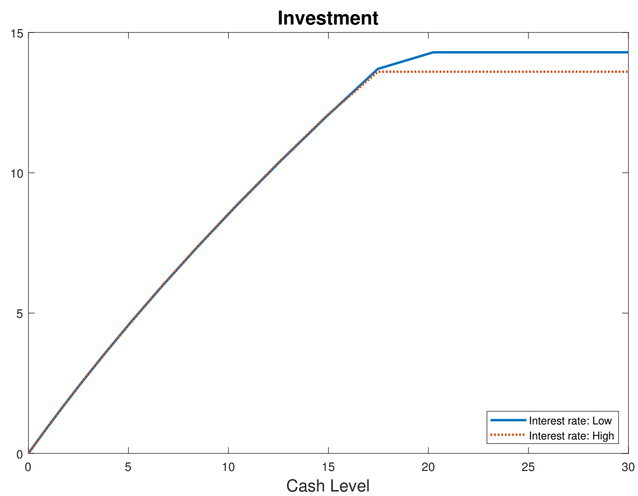
Figure 12 shows the impulse responses of the aggregate variables discussed to the expansionary monetary policy shock constructed in Section 2. The left panel plots the responses of real interest rates, and the right panel plots the responses of real wages. From the figure, we can see that the shocks have persistent effects on the real federal funds rate, which is documented in the previous literature as well.[30] After one standard deviation of expansionary shock, the real interest rate decreases by 40 basis point 1 year after the shock. We can also see that the effect does not disappear over the longer horizon. However, the effect of the shock on real wages seems small both economically and statistically. Therefore, the expansionary interest rate shock is modeled as

[30]See Coibion et al. (2017); Berg et al. (2021).

a persistent increase in the price of patents and a decrease in the real interest rate to align with empirical findings but with no effect on the real wage.

Before moving on to the impulse response of innovation, here, I discuss some features of the optimal firms' policy function for investment, denoted by $\tilde{i}$. Figure 13 plots the investment policy functions of the model against the liquidity. The other state variable, intangible capital, is fixed to the median values from the stochastic simulation. All parameters are set to the calibrated values for the entire sample in Table A.1.

Figure 13: Investment policy function depending on liquidity

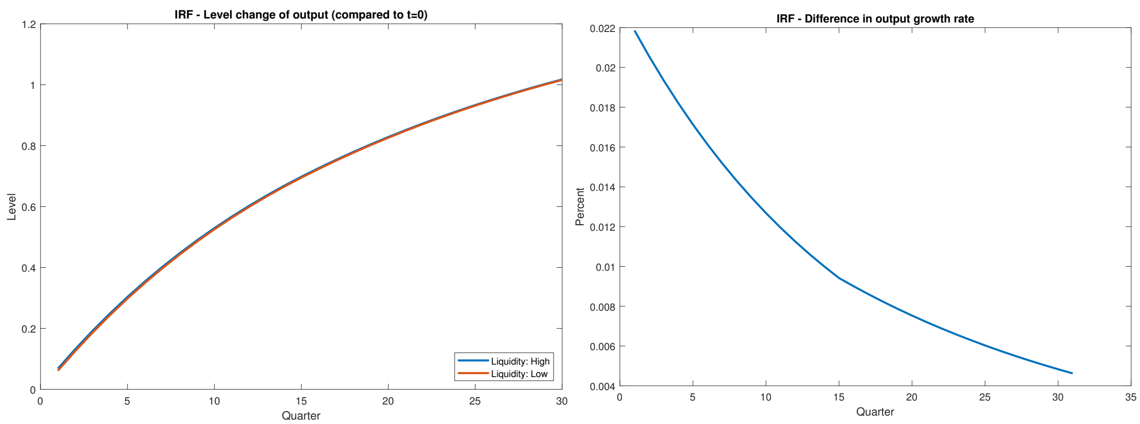


Notes: This figure plots the investment decisions of firms depending on liquidity level

In the panel, I plot two different lines, each showing the policy with a low interest rate and a middle interest rate. The solid blue line plots the policy function with a low interest rate, while the orange dotted line plots the policy function with a middle interest rate. Corporate savings would be unnecessary in the absence of financing frictions, as outside funding could be tapped without additional costs. However, firms face two constraints when accessing the borrowings–the low collateral value of intangible capital and underwriting fees. This makes cash reserves valuable to support upcoming investments. A decrease in the interest rate incentivizes firms to invest more in intangible capital. However, because of the CIA constraint, firms with low liquidity cannot freely choose the optimal level of investment. This causes the positive slope in the policy function. At the same time, because of the dividend non-negativity condition, depending on the level of capital, firms cannot choose the optimal level of cash.

Figure 14 shows the impulse response function of total output depending on the liquidity level. The figure in the Appendix also indicates that the model generates realistic distributions of cash holdings and assets. I use the stationary distribution of cash holdings and set low liquidity as the 10th percentile and high liquidity as the 90th percentile. Productivity is set to be one, while capital is set to the steady-state level of capital. The left panel in the figure plots the responses of innovation depending on liquidity level. The right panel plots the difference between the two. We can see that under this setting, there is no heterogeneity in innovation depending on liquidity level.

Figure 14: Impulse response of innovation to monetary shock



Notes: This figure plots the impulse response of output to 1 standard deviation expansionary monetary policy shock depending on liquidity level.

However, the simulation also provides us with the distribution of productivity depending on cash holdings, which implies that firms with low cash are those that have low productivity and low capital and vice versa. In the data, we can also note that firms with high liquidity accumulate more cash reserves and are more productive compared to firms with low liquidity.

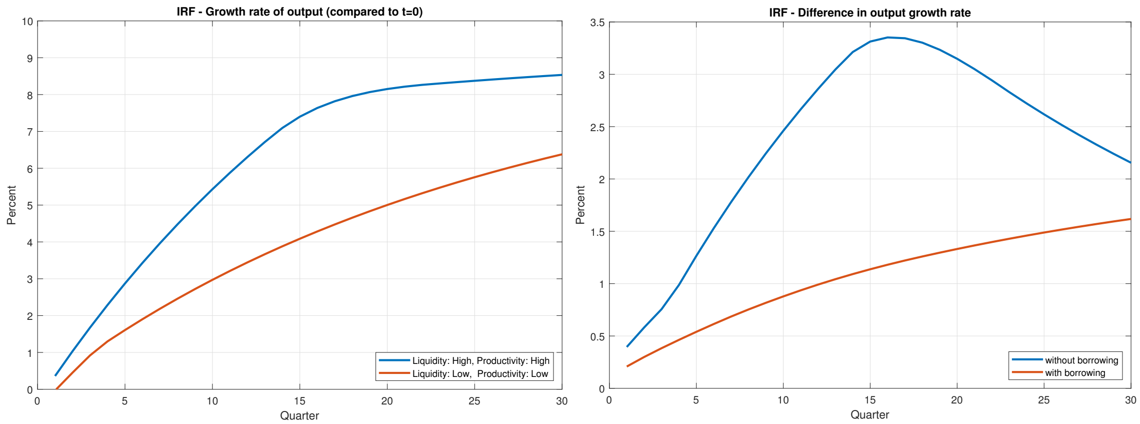
Table 4: Correlation matrix

	Total factor productivity	Patent stock	Liquidity
Total factor productivity	1.00		
Patent stock	0.15	1.00	
	(0.00)		
Liquidity	0.12	0.03	1.00
	(0.00)	(0.00)	
Observations	433091		

Notes: The table computes pairwise correlations of variables based on the constructed firm-level dataset in Section 4.

Table 4 shows the correlation structure of firm-level TFP, patent stock, and liquidity constructed in Section 4. Higher liquidity is positively correlated with higher productivity and higher intangible capital measured with the number of patents. Therefore, I adjust the productivity and capital levels based on the distribution. The result is plotted in Figure 15.

Figure 15: Impulse response of innovation to monetary shock



Notes: This figure plots the impulse response of output to one standard deviation expansionary monetary policy shock depending on liquidity level.

Overall, the model with CIA qualitatively replicates the main empirical findings in Section 4 that firms with high liquidity are the most responsive to expansionary monetary policy shocks in innovation. As the empirical evidence suggests, the model mechanism also works by appreciating the patent value and cash holdings that differ across productivity levels. The persistent difference in output growth rate follows from the persistent reduction in the interest rate. The left panel shows that the model qualitatively explains our main empirical result that the high-liquidity firms have the biggest innovation response to an unexpected decrease in the interest rate. To summarize, the model qualitatively explains vital features of the data. In response to an exogenous interest rate cut, firms with high liquidity can easily access their cash reserves to support their intangible investments in both the data and the model.

6 Conclusion

Innovation has profound effects on the macroeconomic environment. One of the major benefits of innovation is its contribution to economic growth. This in turn implies that it affects the central bank's ability to achieve its mandate, price stability, and maximum employment. In this regard, understanding the mechanism of the transmission of monetary policy shock to innovation is important for the policymakers to make decisions about the interest rate, especially during the recession, to overcome any output hysteresis. In this paper, I use the entire history of U.S. patent data to construct a new measure of innovation to assess the productivity effect of monetary policy shocks. By doing so, I can answer several questions that haven't been clarified due to the limited data availability. Empirically, I document how large the effect of monetary policy shocks on the pricing of new technology is, which explains why we see economically and statistically sizable responses of innovation after expansionary monetary policy shock. Moreover, I provide new findings on the differential effect of monetary policy shocks on firms' innovation depending on their financial status. This behavior is driven by firms with high liquidity due to their ability to access accumulated cash reserves. A model in which intangible investment can be financed only through cash and borrowings can match the data well. In response to an expansionary monetary policy shock, the price of innovation increases, which incentivizes all firms to invest more in intangible capital. However, firms with less liquidity cannot freely choose their optimal level of investment because they have limited access to cash reserves and the credit market. These findings have two important implications for policymakers. The first is that monetary policy can have a persistent impact on the real outcome through innovation, which supports monetary non-neutrality. The second is that the response of innovation to monetary shocks may be magnified over time, as public corporations in the US have steadily increased their cash holdings over the last decades.

References

Acharya, Sushant, Julien Bengui, Keshav Dogra, and Shu Lin Wee. 2022. "Slow recoveries and unemployment traps: Monetary policy in a time of hysteresis." *The Economic Journal* 132 (646):2007–2047.

Aghion, Philippe, John Van Reenen, and Luigi Zingales. 2013. "Innovation and institutional ownership." *American economic review* 103 (1):277–304.

Altınkılıç, Oya and Robert S Hansen. 2000. "Are there economies of scale in underwriting fees? Evidence of rising external financing costs." *The Review of Financial Studies* 13 (1):191–218.

Bauer, Michael D and Eric T Swanson. 2022. "A reassessment of monetary policy surprises and high-frequency identification." Tech. rep., National Bureau of Economic Research.

Belo, Frederico, Jun Li, Xiaoji Lin, and Xiaofei Zhao. 2017. "Labor-force heterogeneity and asset prices: The importance of skilled labor." *The Review of Financial Studies* 30 (10):3669–3709.

Bena, Jan, Miguel A Ferreira, Pedro Matos, and Pedro Pires. 2017. "Are foreign investors locusts? The long-term effects of foreign institutional ownership." *Journal of Financial Economics* 126 (1):122–146.

Benigno, Gianluca and Luca Fornaro. 2018. "Stagnation traps." *The Review of Economic Studies* 85 (3):1425–1470.

Berentsen, Aleksander, Mariana Rojas Breu, and Shouyong Shi. 2012. "Liquidity, innovation and growth." *Journal of Monetary Economics* 59 (8):721–737.

Berg, Kimberly A, Chadwick C Curtis, Steven Lugauer, and Nelson C Mark. 2021. "Demographics and monetary policy shocks." *Journal of Money, Credit and Banking* 53 (6):1229–1266.

Bluwstein, Kristina, Sinem Hacioglu Hoke, and Silvia Miranda-Agrippino. 2020. “When Creativity Strikes: News Shocks and Business Cycle Fluctuations.” .

Bolton, Patrick, Hui Chen, and Neng Wang. 2011. “A unified theory of Tobin’s q, corporate investment, financing, and risk management.” *The journal of Finance* 66 (5):1545–1578.

Brown, James R, Steven M Fazzari, and Bruce C Petersen. 2009. “Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom.” *The Journal of Finance* 64 (1):151–185.

Brown, James R and Bruce C Petersen. 2011. “Cash holdings and R&D smoothing.” *Journal of Corporate Finance* 17 (3):694–709.

Cascaldi-Garcia, Danilo and Marija Vukotić. 2022. “Patent-based news shocks.” *Review of Economics and Statistics* 104 (1):51–66.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans. 2005. “Nominal rigidities and the dynamic effects of a shock to monetary policy.” *Journal of political Economy* 113 (1):1–45.

Chu, Angus C, Guido Cozzi, and Silvia Galli. 2014. “Stage-dependent intellectual property rights.” *Journal of Development Economics* 106:239–249.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico. 2018. “Monetary policy, corporate finance and investment.” Tech. rep., National Bureau of Economic Research.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia. 2017. “Innocent Bystanders? Monetary policy and inequality.” *Journal of Monetary Economics* 88:70–89.

Comin, Diego and Mark Gertler. 2006. “Medium-term business cycles.” *American Economic Review* 96 (3):523–551.

Cook, Timothy and Thomas Hahn. 1989. “The effect of changes in the federal funds rate target on market interest rates in the 1970s.” *Journal of monetary economics* 24 (3):331–351.

Cooper, Russell W and John C Haltiwanger. 2006. “On the nature of capital adjustment costs.” *The Review of Economic Studies* 73 (3):611–633.

Crouzet, Nicolas and Neil R Mehrotra. 2020. “Small and large firms over the business cycle.” *American Economic Review* 110 (11):3549–3601.

Dorn, David, Gordon H Hanson, Gary Pisano, Pian Shu et al. 2020. “Foreign competition and domestic innovation: Evidence from US patents.” *American Economic Review: Insights* 2 (3):357–74.

Döttling, Robin and Lev Ratnovski. 2021. “Monetary policy and intangible investment.” *Available at SSRN 3612304* .

Driscoll, John C and Aart C Kraay. 1998. “Consistent covariance matrix estimation with spatially dependent panel data.” *Review of economics and statistics* 80 (4):549–560.

Evans, Charles L and F Teixeira dos Santos. 2002. “Monetary policy shocks and productivity measures in the G-7 countries.” *Portuguese Economic Journal* 1 (1):47–70.

Falato, Antonio, Dalida Kadyrzhanova, Jae Sim, and Roberto Steri. 2020. "Rising intangible capital, shrinking debt capacity, and the US corporate savings glut." *Journal of Finance, forthcoming* .

Fernald, John. 2014. "A quarterly, utilization-adjusted series on total factor productivity." Federal Reserve Bank of San Francisco.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2016. "Agglomeration of invention in the Bay Area: Not just ICT." *American Economic Review* 106 (5):146–51.

Fornaro, Luca and Martin Wolf. 2020. "The scars of supply shocks." *Available at SSRN 3737556* .

Galí, Jordi. 2022. "Insider–outsider labor markets, hysteresis, and monetary policy." *Journal of Money, Credit and Banking* 54 (S1):53–88.

Garga, Vaishali and Sanjay R Singh. 2021. "Output hysteresis and optimal monetary policy." *Journal of Monetary Economics* 117:871–886.

Gertler, Mark and Simon Gilchrist. 1994. "Monetary policy, business cycles, and the behavior of small manufacturing firms." *The Quarterly Journal of Economics* 109 (2):309–340.

Gertler, Mark and Peter Karadi. 2015. "Monetary policy surprises, credit costs, and economic activity." *American Economic Journal: Macroeconomics* 7 (1):44–76.

Gorodnichenko, Yuriy and Michael Weber. 2016. "Are sticky prices costly? Evidence from the stock market." *American Economic Review* 106 (1):165–99.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson. 2005. "The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models." *American economic review* 95 (1):425–436.

Hall, Bronwyn H. 1990. "The manufacturing sector master file: 1959-1987."

———. 2002. "The financing of research and development." *Oxford review of economic policy* 18 (1):35–51.

———. 2010. "The financing of innovative firms." *Review of Economics and Institutions* 1 (1).

Hall, Bronwyn H, Adam Jaffe, and Manuel Trajtenberg. 2005. "Market value and patent citations." *RAND Journal of economics* :16–38.

Hori, Takeo. 2020. "Monetary policy, financial frictions, and heterogeneous R&D firms in an endogenous growth model." *The Scandinavian Journal of Economics* 122 (4):1343–1373.

Howes, Cooper. 2021. "Financial constraints, sectoral heterogeneity, and the cyclicality of investment." *Federal Reserve Bank of Kansas City Working Paper* (21-06).

İmrohoroğlu, Ayşe and Şelale Tüzel. 2014. "Firm-level productivity, risk, and return." *Management Science* 60 (8):2073–2090.

Jeenas, Priit. 2019. "Firm balance sheet liquidity, monetary policy shocks, and investment dynamics." *Work in progress* .

Jordà, Òscar. 2005. “Estimation and inference of impulse responses by local projections.” *American economic review* 95 (1):161–182.

Jordà, Òscar, Sanjay R Singh, and Alan M Taylor. 2020. “The long-run effects of monetary policy.” Tech. rep., National Bureau of Economic Research.

Kashyap, Anil K, Owen A Lamont, and Jeremy C Stein. 1994. “Credit conditions and the cyclical behavior of inventories.” *The Quarterly Journal of Economics* 109 (3):565–592.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. “Technological innovation, resource allocation, and growth.” *The Quarterly Journal of Economics* 132 (2):665–712.

Koh, Ping-Sheng and David M Reeb. 2015. “Missing r&d.” *Journal of Accounting and Economics* 60 (1):73–94.

Li, Wendy CY and Bronwyn H Hall. 2020. “Depreciation of business R&D capital.” *Review of Income and Wealth* 66 (1):161–180.

Mann, William. 2018. “Creditor rights and innovation: Evidence from patent collateral.” *Journal of Financial Economics* 130 (1):25–47.

Meier, Matthias and Timo Reinelt. 2020. *Monetary policy, markup dispersion, and aggregate TFP*. 2427. ECB Working Paper.

Moran, Patrick and Albert Queralto. 2018. “Innovation, productivity, and monetary policy.” *Journal of Monetary Economics* 93:24–41.

Morlacco, Monica and David Zeke. 2021. “Monetary policy, customer capital, and market power.” *Journal of Monetary Economics* 121:116–134.

Nakamura, Emi and Jón Steinsson. 2018. “High-frequency identification of monetary non-neutrality: the information effect.” *The Quarterly Journal of Economics* 133 (3):1283–1330.

Ottonello, Pablo and Thomas Winberry. 2020. “Financial heterogeneity and the investment channel of monetary policy.” *Econometrica* 88 (6):2473–2502.

Peters, Ryan H and Lucian A Taylor. 2017. “Intangible capital and the investment-q relation.” *Journal of Financial Economics* 123 (2):251–272.

Rampini, Adriano A and S Viswanathan. 2010. “Collateral, risk management, and the distribution of debt capacity.” *The Journal of Finance* 65 (6):2293–2322.

Sharpe, Steven A and Gustavo A Suarez. 2021. “Why isn’t business investment more sensitive to interest rates? evidence from surveys.” *Management Science* 67 (2):720–741.

Sibilkov, Valeriy. 2009. “Asset liquidity and capital structure.” *Journal of financial and quantitative analysis* 44 (5):1173–1196.

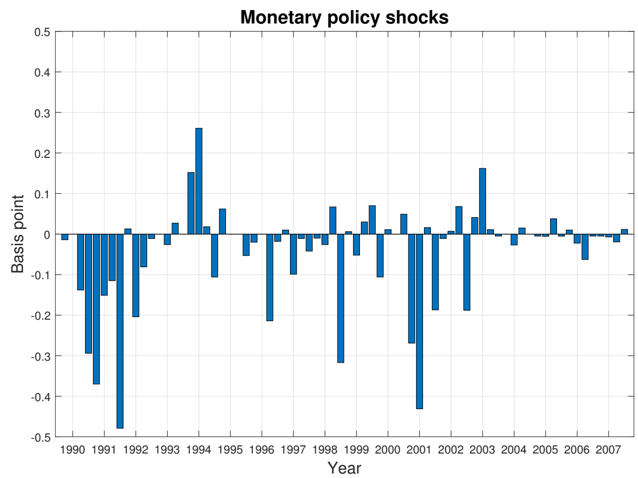
Weiss, Joshua. 2019. “Intangible investment and market concentration.” Tech. rep., Working paper.

Wong, Arlene. 2018. “Transmission of monetary policy to consumption and population aging.” *Manuscript, Princeton University* .

For online publication

A Additional results

Figure A.1: Time series of the monetary policy shock

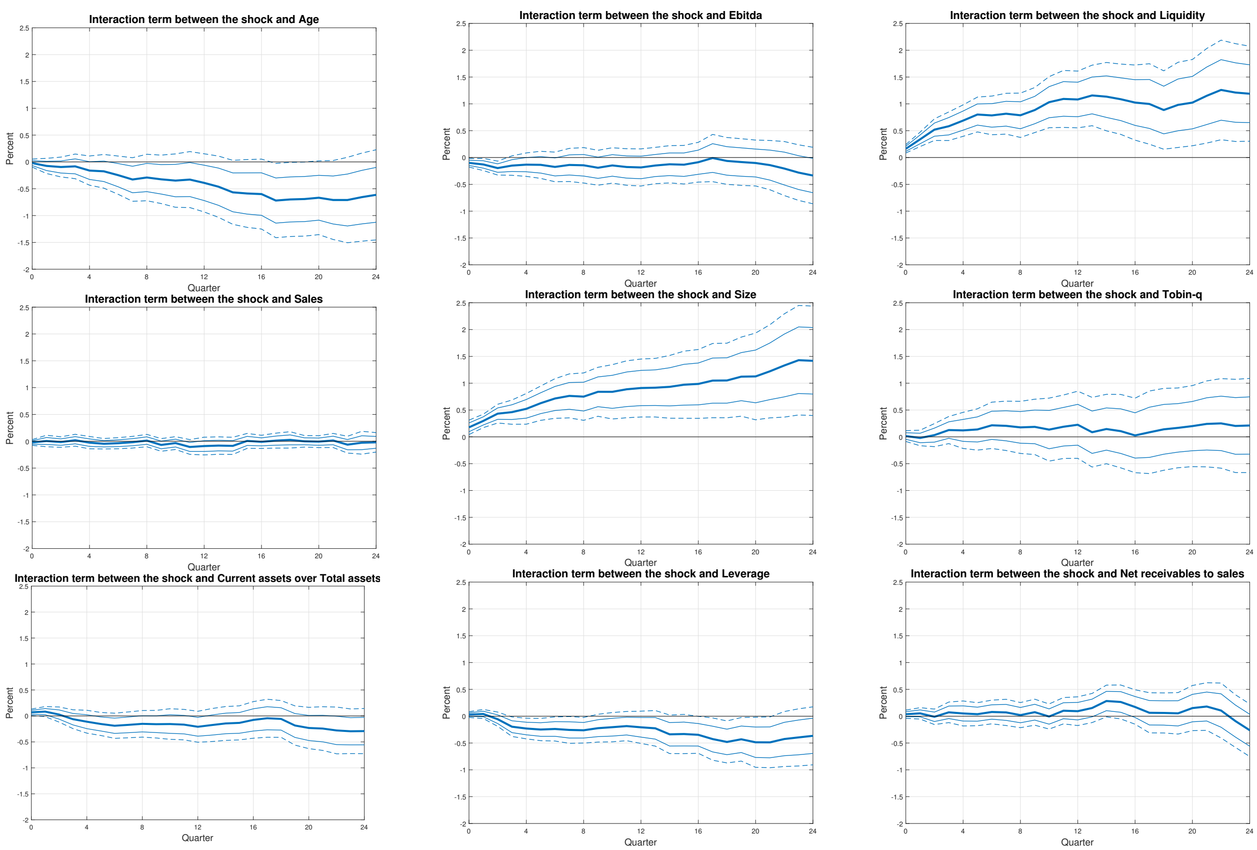


Notes: This figure plots the time series of the monetary policy shock measured by the high-frequency method following Ottonello and Winberry (2020) which is used as a baseline measure of monetary policy shocks in the main analysis. The sample period starts from 1990 to 2007.

Table A.1: Baseline Calibration

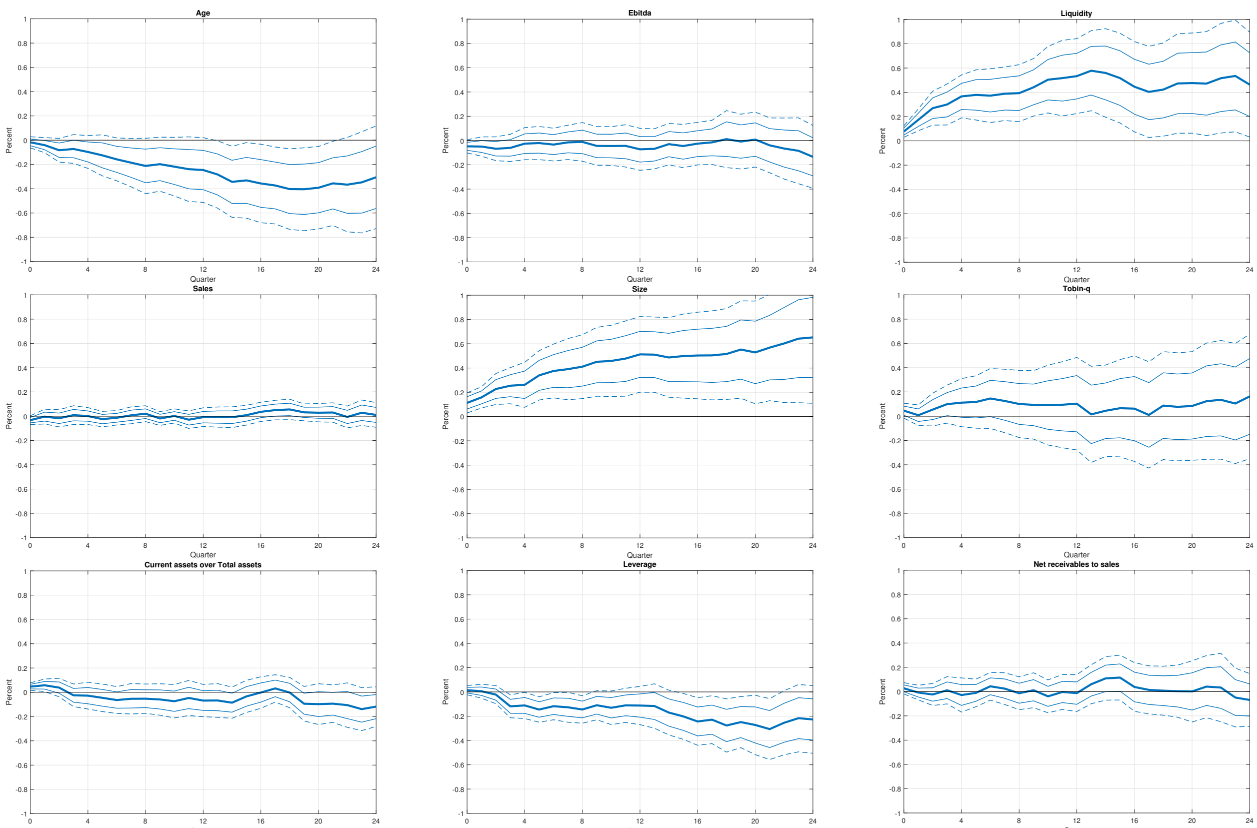
Description	Calibration	Source
Technology		
Curvature of profit function (α)	0.6	Hennessy and Whited (2005,2007)
Depreciation of intangible capital (δ)	0.05	Average depreciation of intangible capital (data)
Fixed cost of intangible capital adjustment (F^i)	0.04	Belo et al. (2017)
Convex parameters in intangible capital adjustment (c^i)	3.1	Belo et al. (2017)
Finance		
Collateral rate of intangible capital (θ)	0.28	Sun and Xiaolan (2019)
Fixed cost of bond issuance (F^L)	0.07	Benzoni, Garlappi, and Goldstein (2022)
Stochastic process		
Persistence of productivity (ρ)	0.90	Ottonello and Winberry (2020)
Standard deviation of innovations to productivity (σ)	0.03	Ottonello and Winberry (2020)

Figure A.2: Heterogeneous impulse responses after expansionary shocks



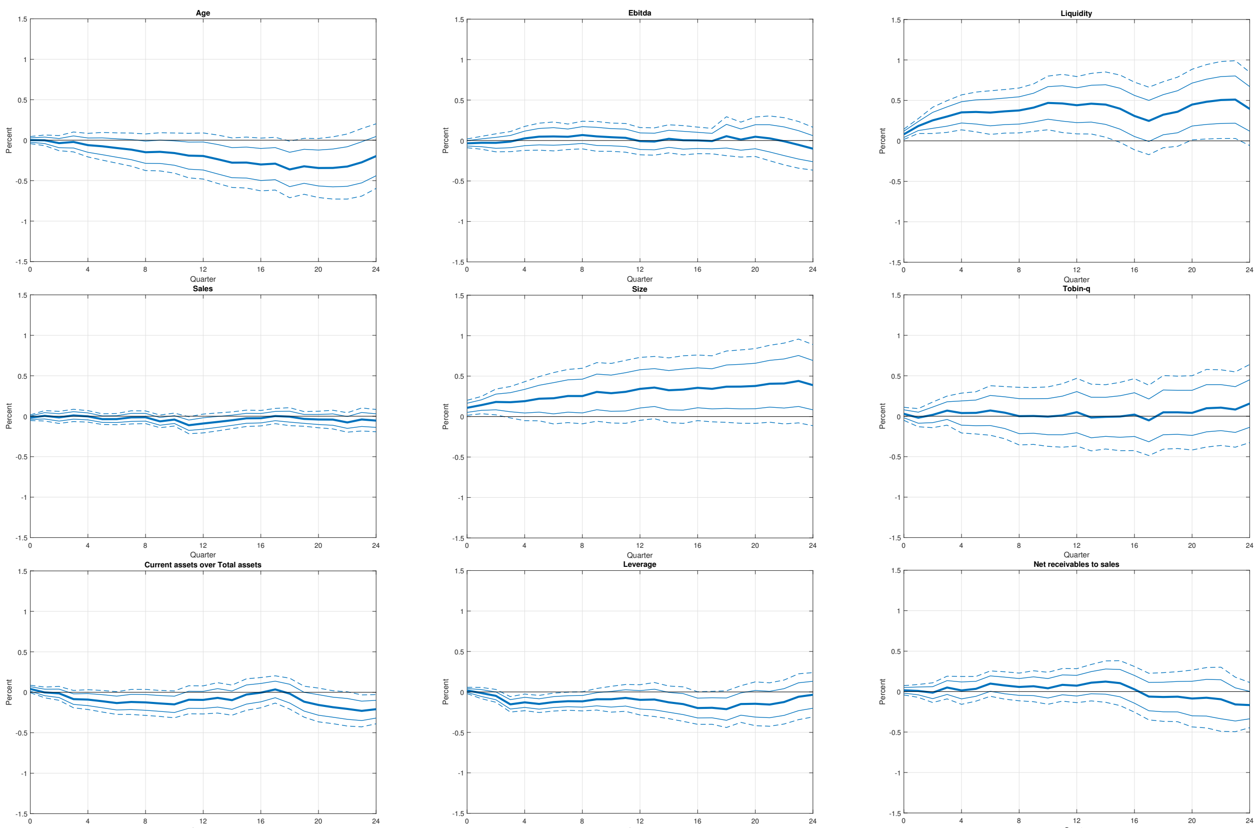
Notes: This figure plots the dynamics of the interaction term between all firm control variables and monetary policy shock based on the specification 3

Figure A.3: Heterogeneous impulse responses after expansionary shocks



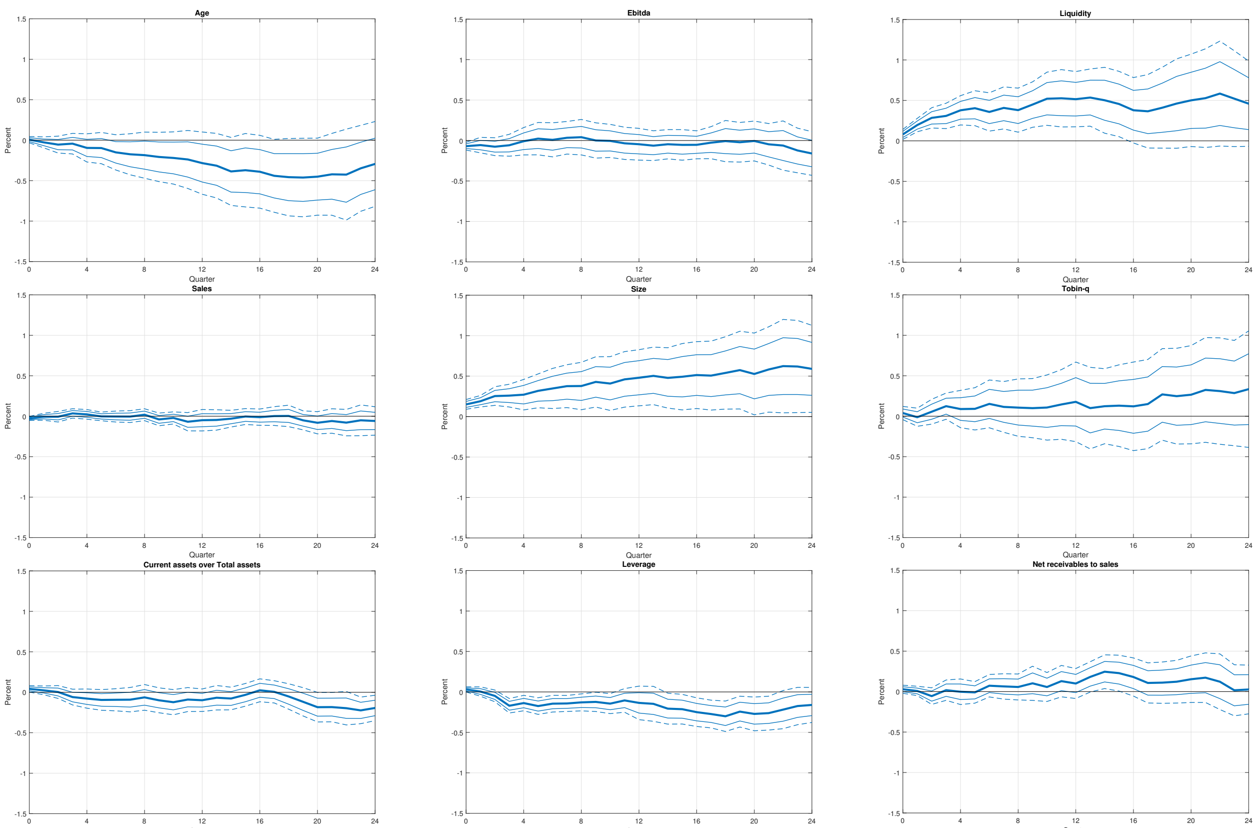
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3 with the monetary policy shock measured with the method proposed by Gertler and Karadi (2015)

Figure A.4: Heterogeneous impulse responses after expansionary shocks



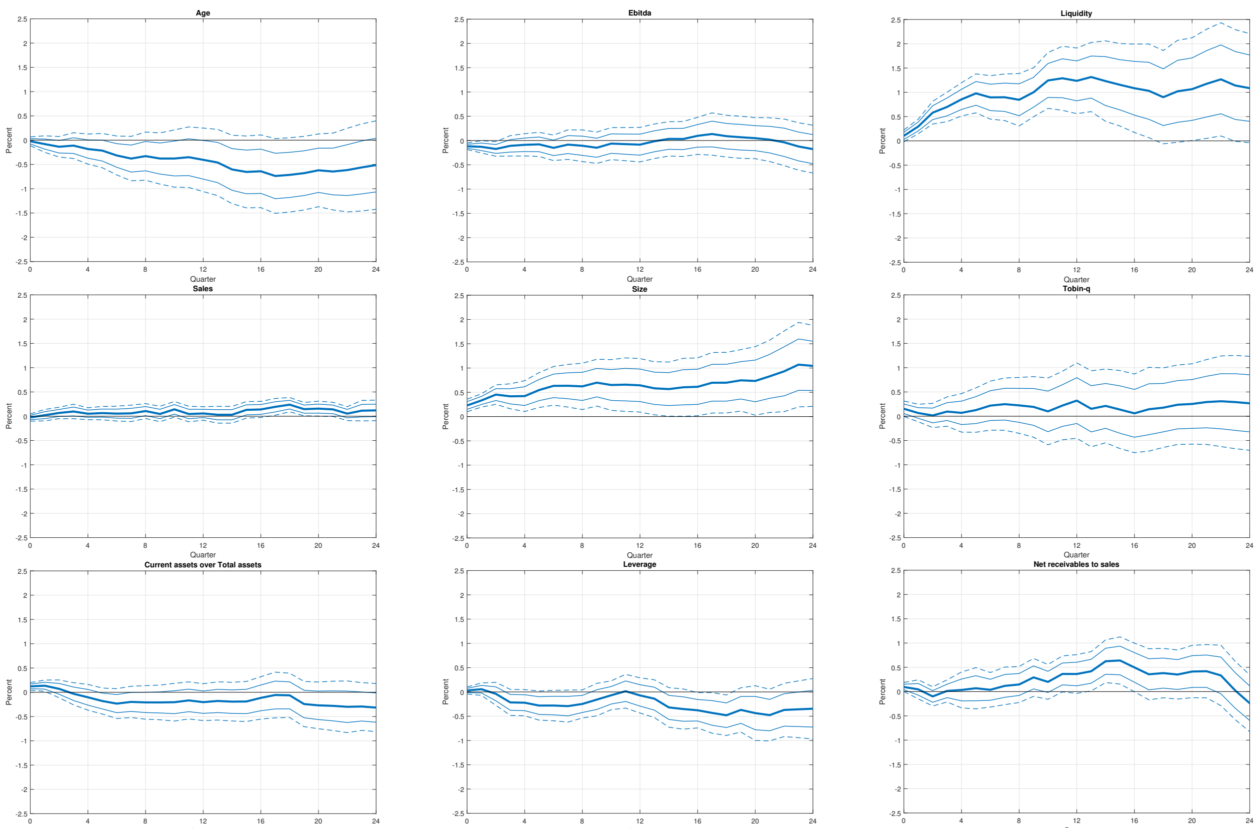
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3 with the monetary policy shock measured with the method proposed by Nakamura and Steinsson (2018)

Figure A.5: Heterogeneous impulse responses after expansionary shocks



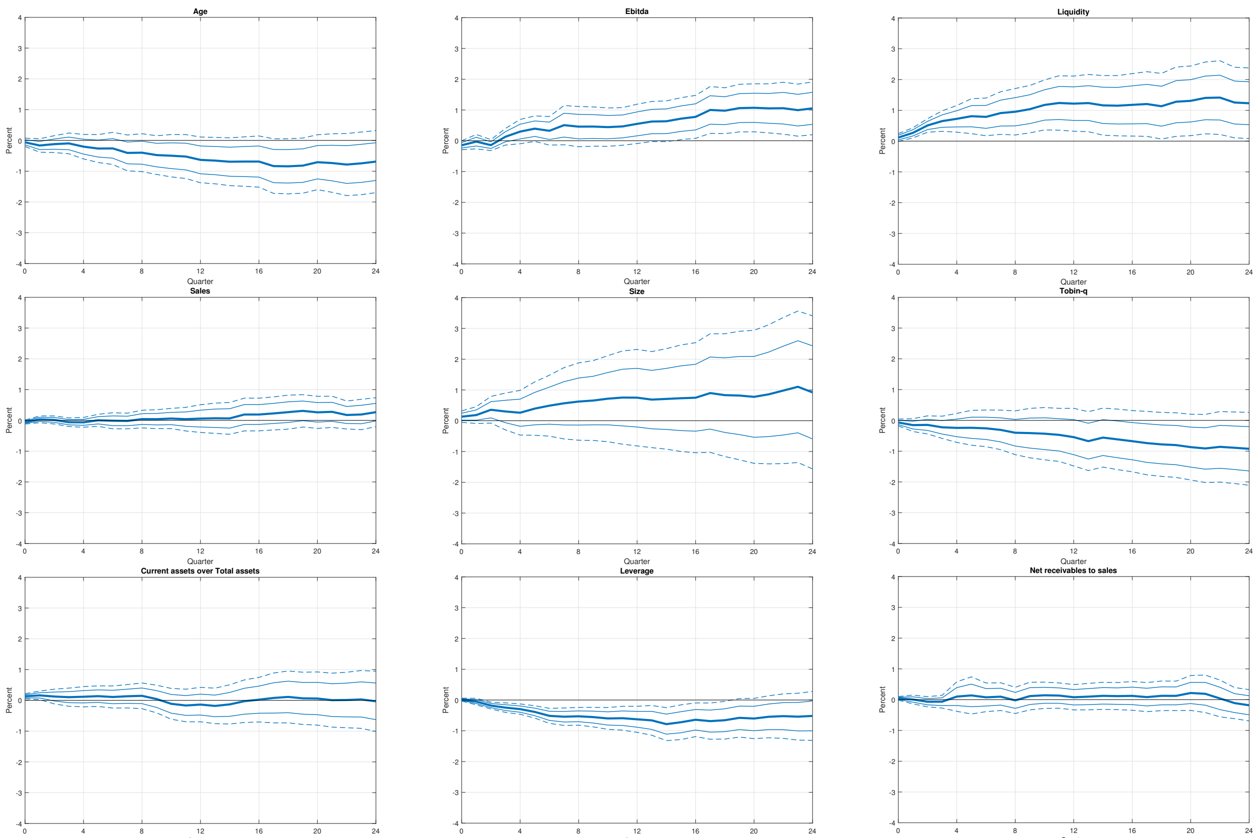
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3 with the monetary policy shock measured with the method proposed by Bauer and Swanson (2022)

Figure A.6: Heterogeneous impulse responses after expansionary shocks



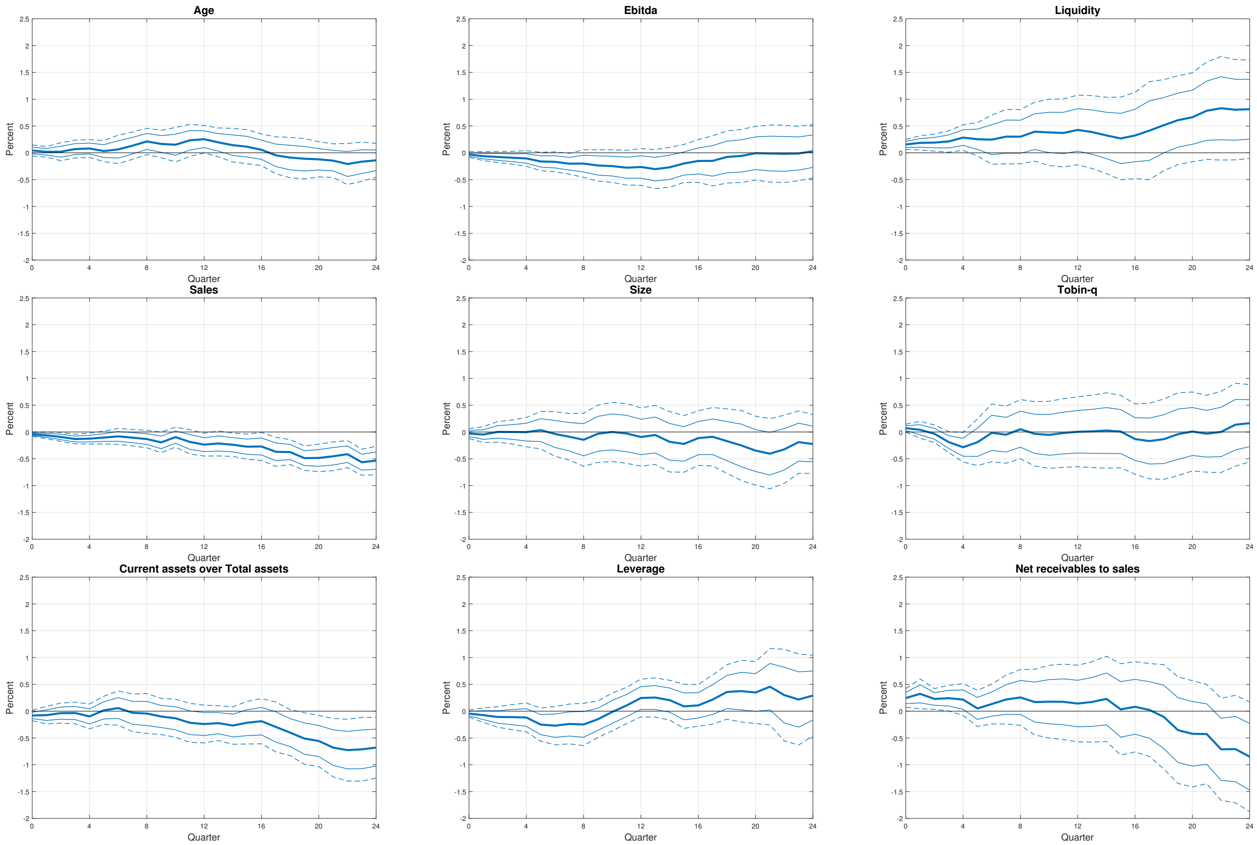
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3. Innovation measure is constructed based on the number of citation.

Figure A.7: Heterogeneous impulse responses after expansionary shocks



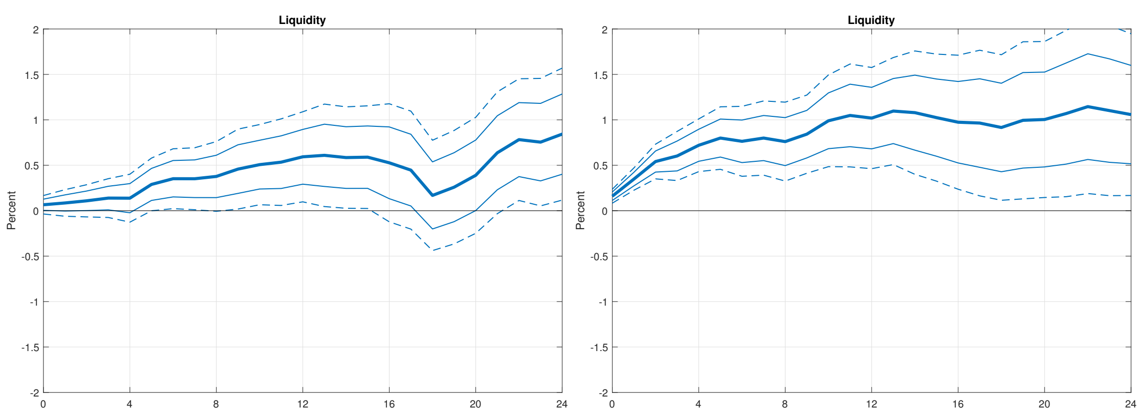
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3. Innovation measure is constructed based on the economic value of each patent estimated in Kogan et al. (2017).

Figure A.8: Heterogeneous impulse responses after expansionary shocks



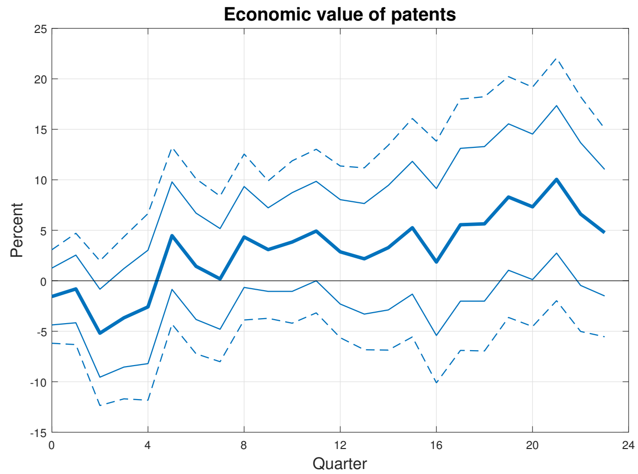
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3. Innovation measure is constructed based on the R&D from Compustat.

Figure A.9: Heterogenous impulse responses after contractionary / expansionary shocks



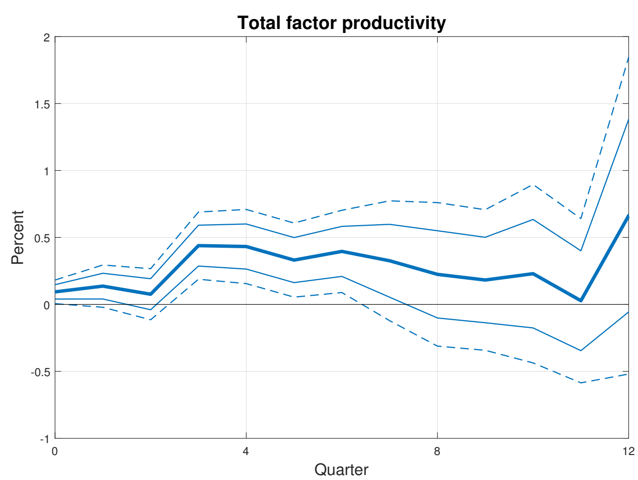
Notes: This figure plots the dynamics of the interaction term between firm control variables and monetary policy shock based on the specification 3 but using ε_t^{m-} and ε_t^{m+} instead of ε_t^m. Left panel plots the coefficient of contractionary shock and the right panel plots the coefficient of expansionary shock.

Figure A.10: Impulse response function of economical value of patents



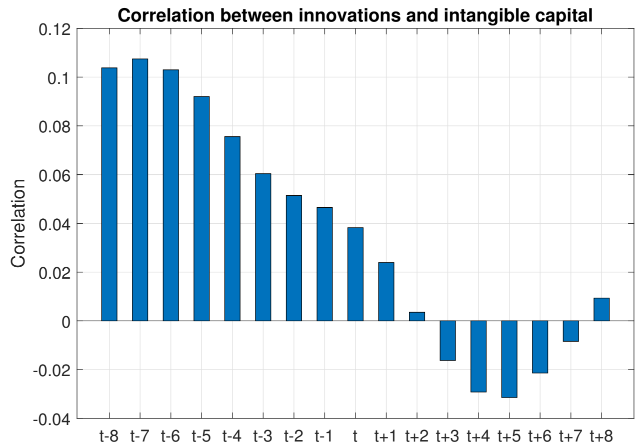
Notes: This figure plots difference in the estimates of effect of expansionary monetary policy shock on patent value between high-liquidity group and low-liquidity group.

Figure A.11: Effect of patent application on TFP



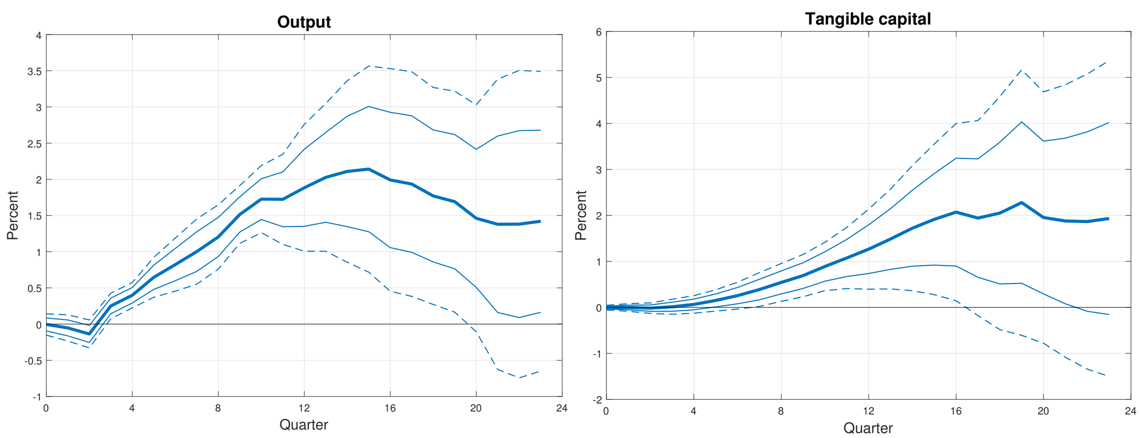
Notes: This figure plots the impulse response of TFP to changes in patent application. In particular, I use the specification as follows. $\log(x_{t+h}) - \log(x_{t-1}) = c^h + \sum_{j=1}^{J} \alpha_j^h \left(\log(x_{t-j}) - \log(x_{t-j-1})\right) + \sum_{i=0}^{I} \beta_i^h (\log(z_{t-i}) - \log(z_{t-i-1})) + u_{t+h}$ where x denotes TFP and z denotes patent application. β_i^h is plotted in the figure.

Figure A.12: Correlation between innovation and intangible capital



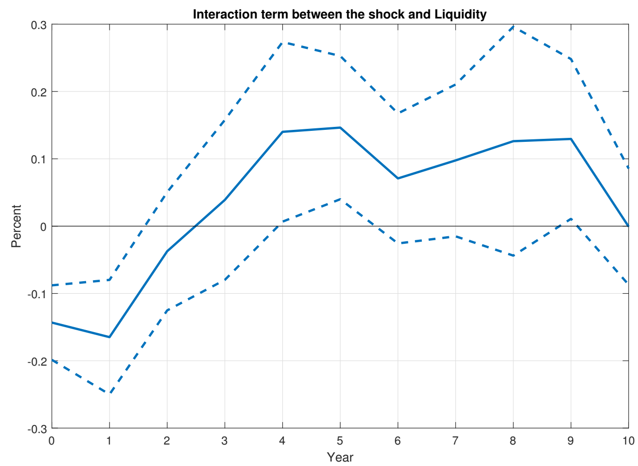
Notes: This figure plots the correlation between Patent stock$_t$ and Intangible capital stock$_{t+j}$ where j = -8, ..., 8

Figure A.13: Impulse Responses of Aggregates to Expansionary Monetary Policy



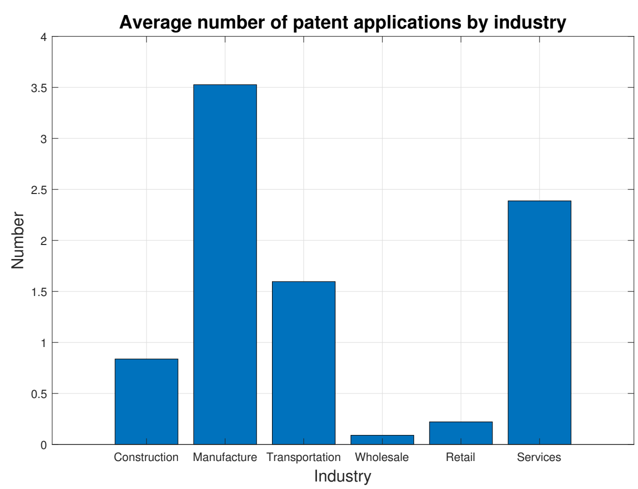
Notes: This figure plots the impulse responses of aggregates to a negative, one standard deviation monetary policy shock using the local projections method Jordà (2005). Quarterly TFP is from Fernald (2014) and monetary policy shock is from Gertler and Karadi (2015). For details, we use the exact specification as in Coibion et al. (2017). Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.14: Dynamics of differential response to monetary shocks on productivity



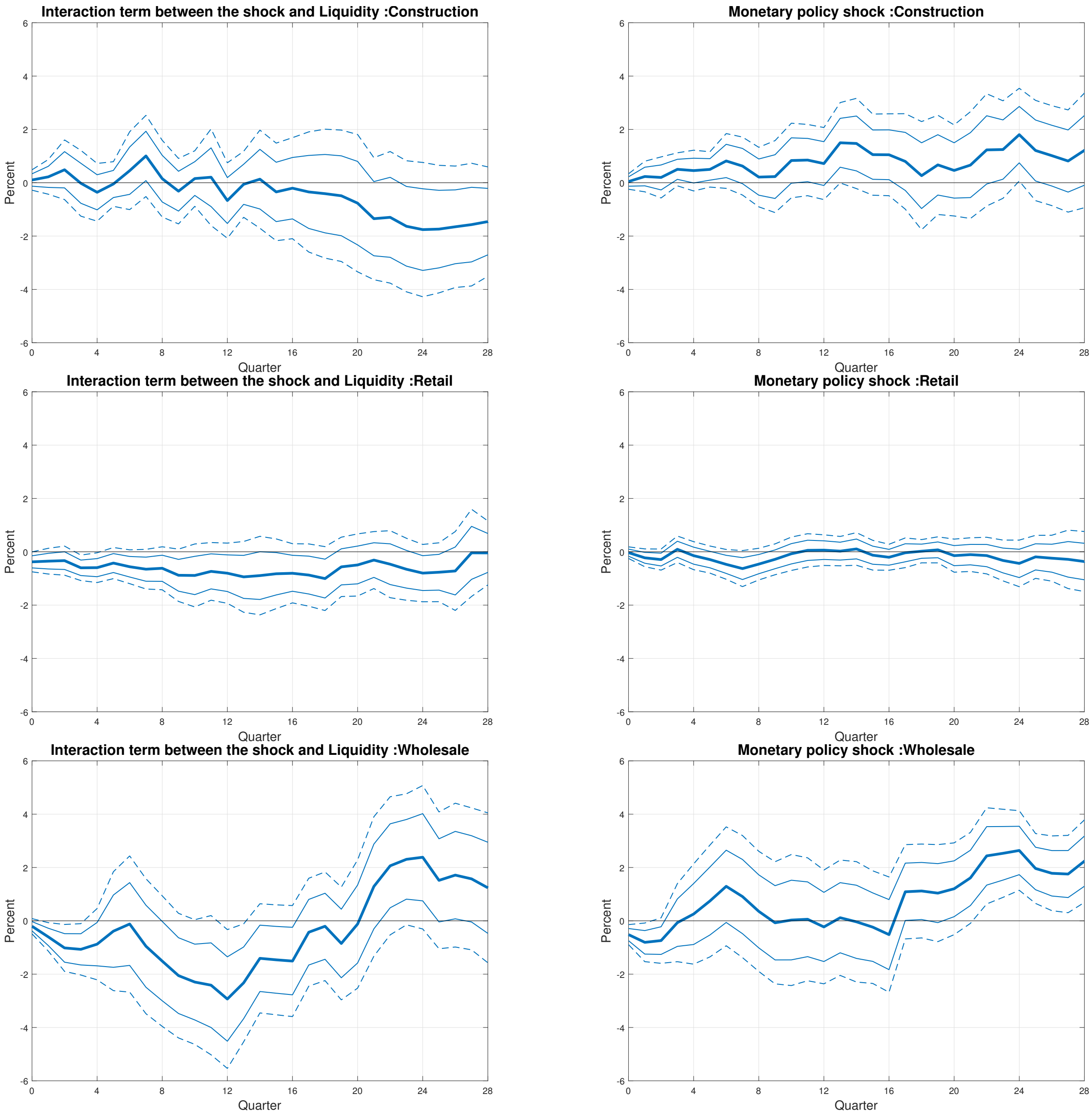
Notes: This figure plots the dynamics of the coefficient of interaction term between liquidity and monetary policy shocks based on the specification (3). Dotted line displays the one standard deviation confidence interval.

Figure A.15



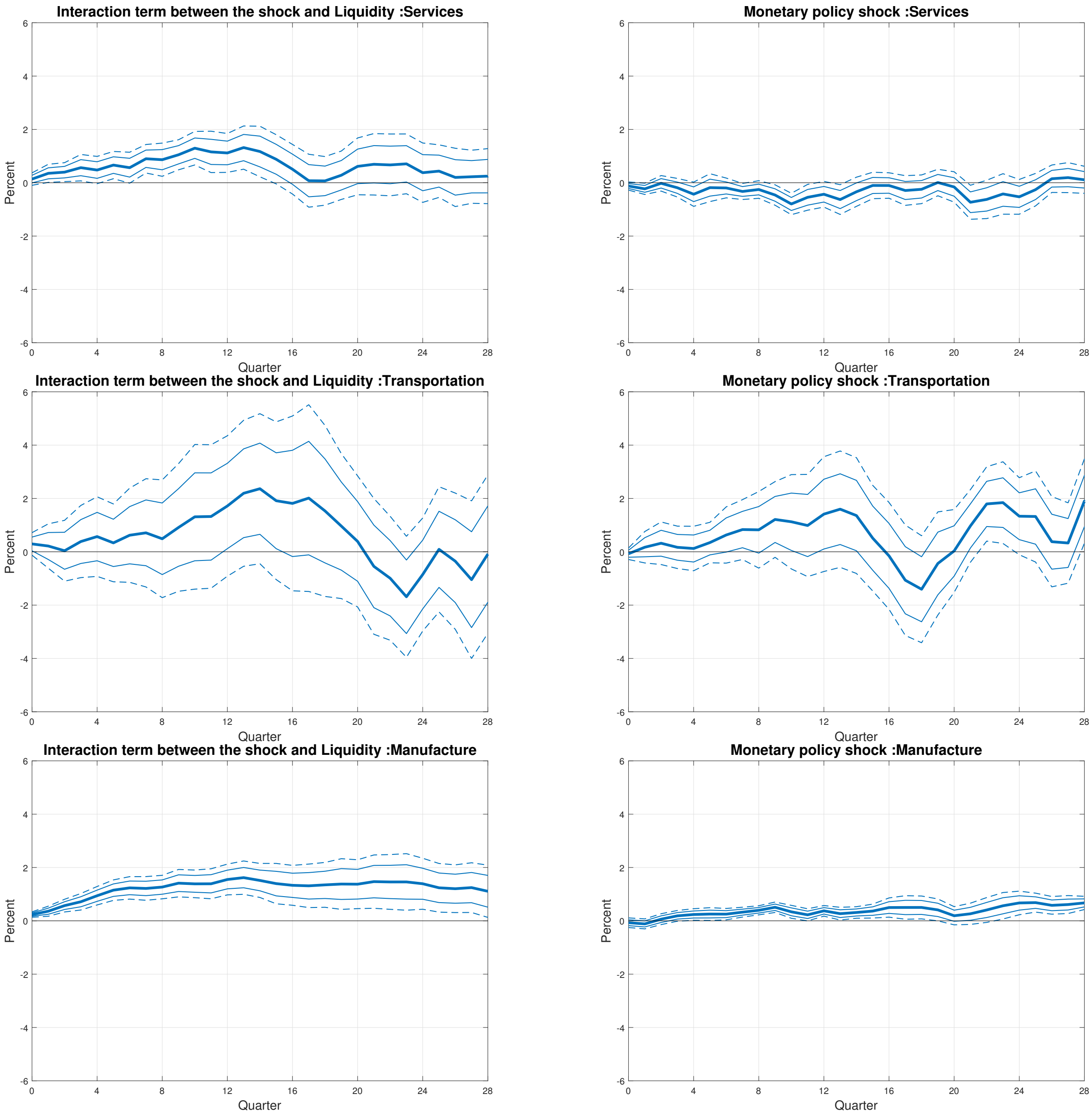
Notes: This figure plots the average number of patent applications by each industry using SIC 1 digit.

Figure A.16: Dynamics of differential response to monetary shocks on productivity



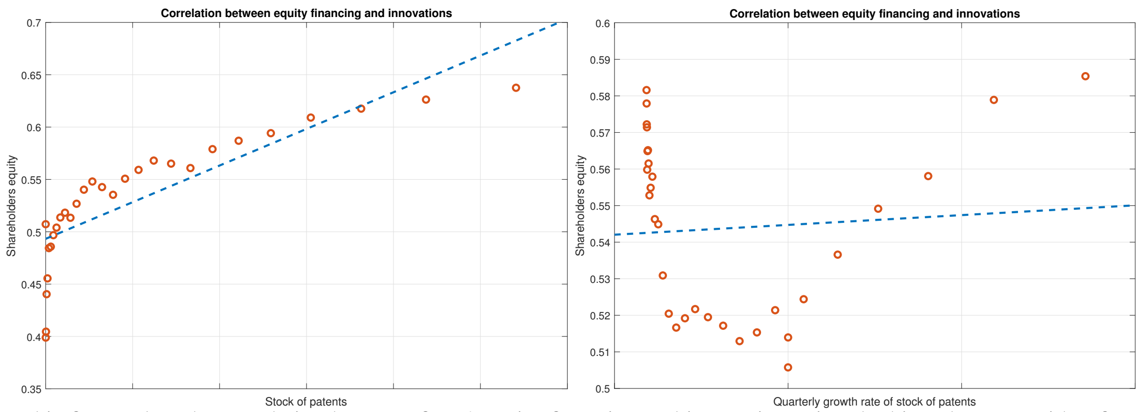
Notes: This figure plots the dynamics of the coefficient of interaction term between liquidity and monetary policy shocks based on the specification (3) by each industry using SIC 1 digit. Dotted line displays the one standard deviation confidence interval.

Figure A.17: Dynamics of differential response to monetary shocks on productivity



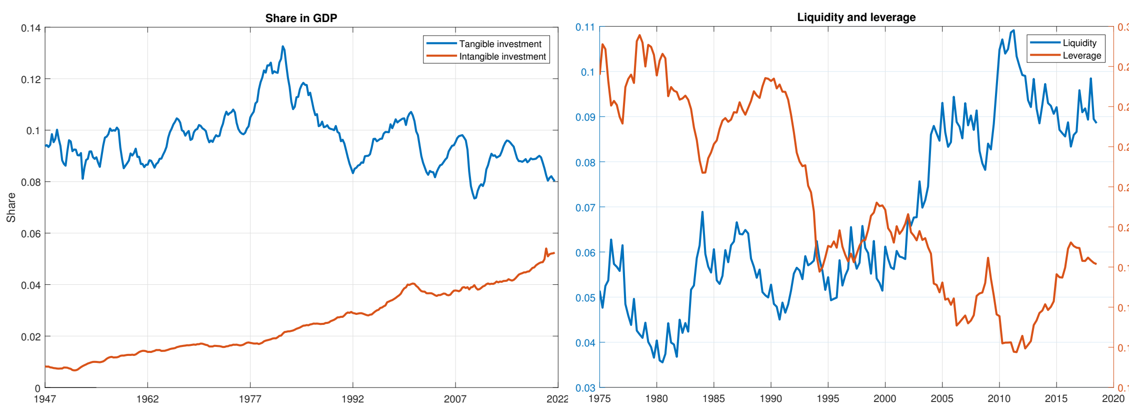
Notes: This figure plots the dynamics of the coefficient of interaction term between liquidity and monetary policy shocks based on the specification (3) by each industry using SIC 1 digit. Dotted line displays the one standard deviation confidence interval.

Figure A.18: Correlation between equity financing and innovations

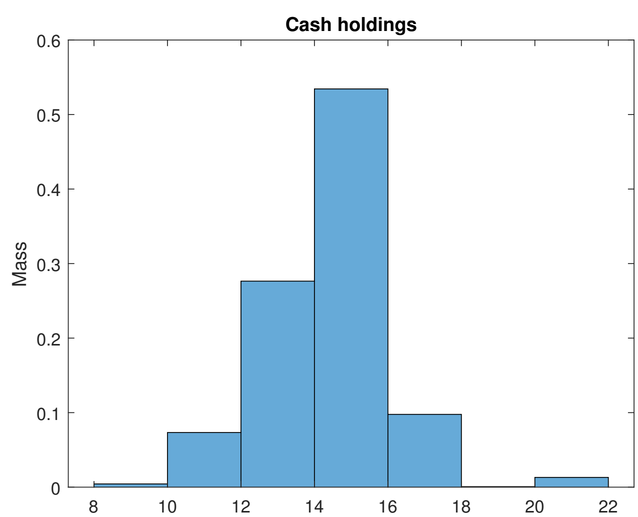


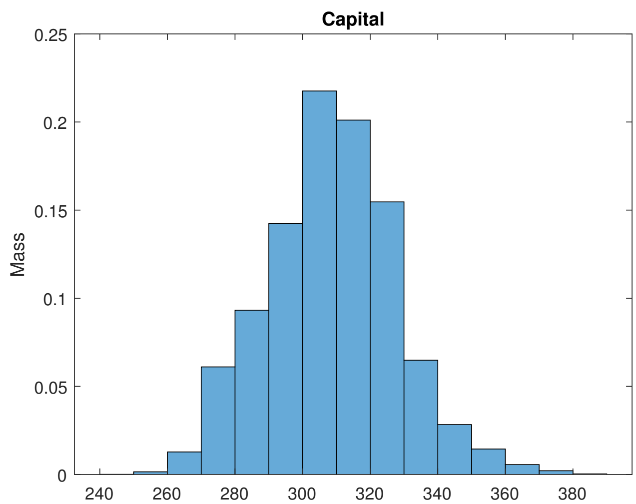
Notes: This figure plots the correlation between firms' equity financing and innovation using the binned scatter with a fitted line. The left panel use patent stock which is divided by firms' total asset for normalization and the right panel use the growth rate of patent stock as a measure of innovation.

Figure A.19: Time-series of intangible investment, liquidity, and leverage



Notes: This figure plots the evolution of the share of intangible investment in GDP, liquidity, and leverage. I used NIPA table to calculate the share of intangible investment in the left panel and Compustat to calculate the average liquidity and the leverage in given quarter in the right panel




Capital
Mass
0.25
0.2
0.15
0.1
0.05
0
240
260
280
300
320
340
360
380

B Data construction

In this subsection, I provide details on the construction of the firm-level variables. I provide a list of firm control variables as well as industry classification used in the paper.

B.1 Balance sheet data

Firm control variables

Below is the list of firm control variables used and how they are constructed in the main analysis.

Table B.1: construction of firm-level variables

Variable	Construction		Sources
	Details	From the data	
Liquidity	$\frac{\text{cash and short-term investment}}{\text{total assets}}$	$\frac{CHEQ_{i,t}}{ATQ_{i,t}}$	Compustat
Leverage	$\frac{\text{total debt}}{\text{total assets}}$	$\frac{DLCQ_{i,t}+DLTTQ_{i,t}}{ATQ_{i,t}}$	Compustat
Age	based on the incorporation date		WorldScope
Size	book value of assets	$\log(ATQ_{i,t})$	Compustat
EBITDA		$100*\frac{SALEQ_{i,t}-COGSQ_{i,t}-XSGAQ_{i,t}}{IPD_{i,t}}$	Compustat
Tobin's Q		$\frac{ATQ_{i,t}+PRCCQ_{i,t}*CSHOQ_{i,t}-CEQ_{i,t}+TXDITCQ_{i,t}}{ATQ_{i,t}}$	Compustat
Real sales growth		$100*\Delta\log(100*\frac{SALEQ_{i,t}}{IPD_{i,t}})$	Compustat
Net receivables to sales		$\frac{RECTQ_{i,t}-APQ_{i,t}}{SALEQ_{i,t}}$	Compustat
Current assets over total assets		$\frac{ACTQ_{i,t}}{ATQ_{i,t}}$	Compustat

Notes: This table provides details of construction of firm-level variables used in the main analysis.

Sectoral dummies

1. Agriculture, forestry, and fishing: SIC < 999
2. Mining: SIC $\in$ [1000, 1499]
3. Construction: SIC $\in$ [1500, 1799]
4. Manufacturing: SIC $\in$ [2000, 3999]
5. Transportation, communications, electric, gas, and sanitary services: SIC $\in$ [4000, 4999]

6. Wholesale trade: SIC $\in$ [5000, 5199]
7. Retail trade: SIC $\in$ [5200, 5999]
8. Services: SIC $\in$ [7000, 8999]

Tangible capital stock

I construct tangible capital based on the perpetual inventory method following previous literature (Ottonello and Winberry, 2020). From Compustat, I use PPEGTQ (Property,Plant and Equipment (Gross)) and PPENTQ (Property, Plant and Equipment (Net))

1. Set initial capital as first observation of PPEGTQ
2. Linearly interpolate PPENTQ
3. Construct capital stock

B.2 Patent

Construct patent stock based on the number of citation

It is clear that the two different patents unlikely to have same values. However, if the innovation measure is constructed based on the number of patents, each patent will have the same "economically" importance so that the innovation measure is not accurately constructed. That is why using the number of patents as an instrument might not be relevant in this paper. To deal with this issue, literature provide citations of patent as a solution. If firms invest in innovations disclosed in a previous patent, the resulting patents presumably signify that the cited innovation is economically valuable. In that sense, using the number of citations as a baseline measure to construct stock of knowledge capital is appropriate. To use citation properly, I scaled the number of citation the patent has with number of forward citations received by the patents that were applied in the same year as patent j. Table B.2 shows why scaling is necessary.

Table B.2: How Amazon filed its patents

1995 Q1		2004 Q1	
patent id	citation	patent id	citation
05727163	486	07194419	78
		07254552	31
		07466875	21
		07433835	39
		07536322	108
	486		277

Notes: This table shows how Amazon filed their patents in 1995Q1 and 2004Q2

In 1995Q1, Amazon filed only one patent. In 2004Q1, they filed fives. In terms of number of citation, it seems like the patent filed in 1995 outweigh those that are filed in 2004 because the number of citation given to the patent filed in 1995 is greater than the total number of citations of patents filed in 2004. However, one thing to note is that there are two reasons why the patent from 1995 has such high number of citations. First, the patent in 1995 might be more valuable than others. Second, the number of citations simply reflect the fact that the patent is filed earlier. If is the latter case, then the patents filed in earlier days naturally have higher value which should be avoided in the purpose of the paper. To estimate the value of patents accurately, I scale the number of citations as follows.

$$f_{j,t} = \sum_{k \in \text{group of patents}_{j,t}} \left(1 + \frac{C_k}{\bar{C}_t}\right)$$

C_k is the number of forward citations received by the patent k. $\bar{C}_t$ is the average number of forward citations received by the patents that were applied at time t. Then the value of patents in 1995 is $1 + \frac{486}{32} = 16.1875$ and in 2004 the value is $5 + \frac{78+31+21+39+108}{14} = 24.785$ which implies that the patents filed in 2004 is much more valuable than the one from 1995.

The rest of steps are the same as when tangible capital is constructed. To make citation-weighted patent stocks, I have used a depreciation rate of 15% which is a standard in the literature.

$$x_{j,t} = (1-\delta) \cdot x_{j,t-1} + f_{j,t}$$

Lastly, inverse hyperbolic sine transformation is used to use dependent variables as log change of stock

$$P_{j,t} = \log(x_{jt} + \sqrt{x_{jt}^2 + 1})$$

B.3 Sample construction

Merging datasets

To address the main question, I have merged the patent data of the entire history of the U.S. and a quarterly firm level panel of U.S. publicly traded firms. The patent data provided by USPTO use the variable *lpermno* to classify firms. However, compustat uses gvkey as an identifier. In this paper, I employ all the matching algorithm that were used to merge patent data and compustat (Bena et al., 2017; Kogan et al., 2017; Dorn et al., 2020) to cover the period as much as possible.

Sample selection

After merging patent data and balance sheet data, I follow Ottonello and Winberry (2020) to construct the sample for the main analysis. Firm-quarter observations below are excluded in the sample.

1. Firms not incorporated in the United States

2. Firms in finance, insurance, and real estate sectors(SIC code between 6000 and 6700) and utilities (SIC code between 4900 and 4999)

3. One of the firm characteristics is missing in the data

4. Observations before 1990Q1 or after 2011Q4

After applying these sample selection operations, we winsorize every firm-level variable at the top and bottom 0.5% of the distribution.

B.4 Estimating the economic value of patent

To show how the value of innovation changes, I use the economic value of each patent. The method was proposed by Kogan et al. (2017). In this section, I summarize how the value was estimated for illustration purposes.

Estimation

This method uses firms' stock market reaction around their new patent grant date to estimate the economic value of each patent. Hence, it is crucial to isolate the component of stock market movement around the patent grant date that is only related to the value of the patent. Suppose we have a 3-day return for newly granted patent j, R_j starting from the new patent grant date. Then, this value can be decomposed into v_j, which is the value of patent j, and ε_j, which is the component that is not relevant to the patent. Here the economic value of patent p_j is estimated as follows.

$$p_j = (1-\bar{\pi})^{-1} \frac{1}{N_j} E\left[v_j \mid R_j\right] M_j$$

M_j denotes market capitalization, $\bar{\pi}$ denotes the unconditional probability of patent application being successful, and N_j denotes the number of patents that are issued to the same firm on the same day as patent j. The value of the patent was divided equally if a firm issued more than one patent on the same day. Then the method adds one assumption about the distribution of r_j, and ε_j that $v_j \sim N^+\left(0, \sigma^2_{vft}\right)$ and $\varepsilon_j \sim N\left(0, \sigma^2_{\varepsilon ft}\right)$. Then we can rewrite the value v_j as follows.

$$E\left[v_j \mid R_j\right] = \delta_{ft} R_j + \sqrt{\delta_{ft}} \sigma_{\varepsilon ft} \frac{\phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\varepsilon ft}}\right)}{1-\Phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\varepsilon ft}}\right)}$$

where $\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft}+\sigma^2_{\varepsilon ft}}$. Kogan et al. (2017) further assume that this value is constant, meaning that σ^2_{vft} and $\sigma^2_{\varepsilon ft}$ can vary across time and firms but with a fixed ratio. Then the constant δ_{ft} was estimated based on the regression below.

$$\log\left(R_{fd}\right)^2 = \gamma I_{fd} + cZ_{fd} + u_{fd},$$

R_{fd} denotes the idiosyncratic return of firm f starting on day d, I_{fd} denotes whether a new patent was granted, and Z_{fd} denotes other control variables. Then δ_{ft} can be estimated based on γ.