Firm liquidity and the innovation channel of monetary policy *

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Abstract

I provide new empirical evidence against long-run monetary neutrality and document where this non-neutrality originates: innovation. Expansionary monetary policy shocks enhance the value of innovation by lowering discount rates and ultimately leads to an increase in patent filings. As a result, even transitory monetary policy shocks affect the long-run level of total factor productivity (TFP). An analysis at the firm-level also reveals distinct innovation responses along several dimensions. I show that the innovation channel is predominantly driven by firms with high liquidity, which allows them to cover the costs of adjusting their investments for innovation.

Keywords: Monetary policy, Intangible capital, Endogenous technology, Firm balance sheets, Firm heterogeneity

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"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 only affects real outcomes in the short run rendering the central bank incapable of influencing productivity. Nevertheless, recent work has begun to question this assumption: Moran and Queralto (2018) and Jordà, Singh, and Taylor (2020) challenge the notion of long-term monetary neutrality and speculate about the potential causes of a lasting impact of monetary policy shocks on productivity.

In the context of examining the productivity effects of monetary policy, it's crucial to explore how these policies influence innovation. However, we know little about how firms innovate in response to monetary policy changes 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. Utilizing these metrics, I present novel evidence against the notion of long-term monetary neutrality. I also identify a key factor that can explain this observation: endogenous innovation decisions on the part of firms. My findings lend support to Janet Yellen's hypothesis that the impact of monetary policy extends beyond short-term stabilization goals and can foster long-term productivity growth.[1]

A substantial body of recent literature (Kogan et al., 2017; Bluwstein, Hacioglu Hoke, and Miranda-Agrippino, 2020; Cascaldi-Garcia and Vukotić, 2022) has demonstrated a causal link between patent applications and productivity. This suggests that patent applications can serve as a reliable proxy for gauging success in generating knowledge capital, rendering them an ideal measure for achieving the objectives of this study. I use comprehensive patent history data, along with monetary policy shock data, to investigate two research questions. First, does monetary policy affect innovation? And, if so, which firms' innovate in response to monetary policy shocks?

I first provide aggregate empirical evidence using local projections (see Jordà (2005)). From the aggregate point of view, I reevaluate earlier findings that suggest that expansionary monetary policy shocks lead to an increase in long-term Total Factor Productivity (TFP). Following a one standard

[1]Recent examples of research supporting this idea include studies by Benigno and Fornaro (2018); Fornaro and Wolf (2020); Garga and Singh (2021); Galí (2022); Acharya et al. (2022).

deviation expansionary monetary policy shock, TFP grows by 2% over the course of 28 quarters.[2] Then, I offer evidence indicating that this shock gradually and ultimately spurs innovation at the aggregate level, as evidenced by a 1.5% rise in the accumulation of knowledge capital measured through new patent applications.[3] The delayed response of innovation suggests that the post-shock innovation primarily stems from inventing new technologies, rather than patenting existing technologies. Unconditionally, changes in intangible capital generally precede innovations, with a lead time of 2 years, and this timing delay is consistent with what I observe in the conditional impulse responses.

These findings lead to the following question: Why does innovation experience an upswing following expansionary monetary policy shocks? I demonstrate that the economic value of patents increases following a decline in interest rates. I gauge the economic value of each patent using the methodology proposed by Kogan et al. (2017). The mechanism that underlies the aggregated innovation responses to monetary policy shocks is relatively straightforward. Innovations do not necessarily translate to immediate profits upon creation; instead, they yield higher returns in the future. An unexpected reduction in the interest rate augments the value of patents, thereby promoting aggregate innovation. My results reveal a substantial effect of expansionary shocks on patent value; a one standard deviation expansionary shock leads to a remarkable 15% increase in patent value. Previous studies reliant on theoretical models, such as Moran and Queralto (2018), indicate that expansionary monetary policy shocks enhance the value of new technology, albeit to a lesser extent.[4]

Furthermore, I demonstrate that an expansionary monetary policy can lead to the misallocation of capital. This happens because it reduces the costs associated with investing in intangible assets, encouraging companies to invest in technology that might not have been pursued under less favorable conditions. This is evident in the form of a decline in the scientific quality of their work following the policy shock. Additionally, the decrease in the scientific quality of patents implies that the increase in the average economic value of patents can be attributed to a decrease in the discount rate and the economic upswing resulting from expansionary monetary policy shocks. Both of these factors can impact fluctuations in the market value of new patents by enhancing profits derived from patenting innovative technology. Moreover, I find that as innovation increases with the introduction of new patents, the economic value of patents eventually stabilizes. The temporarily elevated returns on innovation lead to a lasting advancement in technological capabilities, which explains the positive long-term TFP response to an expansionary monetary policy shock.

[2] A one standard deviation monetary policy shock raises the effective federal fund rate by 8 basis points.

[3] Subsequent to my paper, Ma and Zimmermann (2023) also look at the effects of monetary policy and confirm my result that monetary policy actions lead to changes in patents and innovation that have long-lived effects on productivity in the U.S.

[4] Moran and Queralto (2018) reports that a 60 basis point expansionary monetary policy shock results in only around a 1% increase in the value of innovation.

It appears that these shocks have had a significant impact on cyclical variations in innovation over the sample period. While the contribution of monetary policy shocks to innovation is almost negligible in short-term forecast error variance decompositions, an analysis of longer time horizons reveals that monetary policy shocks can account for 12 percent of the forecast error variance.

Motivated by the aggregate evidence, I perform a firm-level analysis to clarify the mechanism behind the impact of monetary policy shocks on innovation. I provide cross-sectional evidence on heterogeneous innovation responses 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 various firm-specific variables that have previously been identified as significant factors in explaining heterogeneity in the responses to monetary policy shocks. I find that characteristics such as firm size, age, leverage, and liquidity determine the magnitude of the impact of monetary policy shocks on innovation. Among these attributes, I identify liquidity as a pivotal factor in comprehending this heterogeneity; a one standard deviation increase in liquidity corresponds to a 0.6 percentage point greater increase in innovation following a one standard deviation expansionary monetary policy shock. My estimates are statistically significant and economically sizable, with variations across firms persisting even seven years after the initial shock.

Empirical evidence suggests that the primary reason why firms with ample liquidity exhibit the most pronounced response to the shock is not due to their patents experiencing greater value appreciation or their reliance on external borrowing. Instead, it appears that cash reserves play a key role in financing investment in intangible capital. Financial constraints are widely recognized as significant drivers of fluctuations in tangible capital investments (Ottonello and Winberry, 2020; Howes, 2021) and internal financing from previous cash flows is considered an alternative to external borrowing. However, there is reason to believe that liquidity is of even greater importance for intangible capital. This is because 'asymmetric-information' is likely to elevate the financing costs from external sources (Hall, 2010), and intangible capital lacks collateral value (Falato et al., 2020). In this study, I analyze firms' borrowing data and uncover that there is no variation in firms' borrowing patterns based on the level of liquidity following monetary policy shocks. Nonetheless, when considering adjustment costs, liquidity's significance diminishes for the low capital adjustment costs group, but it remains a crucial factor for the high adjustment costs group. This suggests that companies with ample liquidity can offset their adjustment costs using their cash reserves, which reduces their cost of financing.

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), determine the heterogeneity in responses of tangible capitals. On the other hand, few papers have explored the heterogeneous effect of conventional monetary policy on innovation (see Morlacco and Zeke (2021); Döttling and Ratnovski (2021)). However, these papers study the effects on less precise measures of intangible capital innovation, such as "Selling, General and Administrative Expenses," which contain components that appear to be weakly related to productivity at best. This paper contributes to the literature on the heterogeneity of monetary policy responses by uncovering the role of firm liquidity in innovation behavior after such shocks.

Second, this paper is part of a growing literature on 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, but not on the underlying mechanism. From the aggregate analysis, I confirm that expansionary monetary policy shocks increase TFP. In this respect, this paper is consistent 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). I use a measure of innovation that, while widely used in the literature on innovation, is new to the field of monetary policy. This measure of innovation can explain the productivity effect of monetary policy shocks and provides a new finding that monetary policy shocks have a large impact on the value of innovation. Moreover, the new measure in this paper can be linked to detailed firm-level data, which allows me to study the underlying mechanism. While Meier and Reinelt (2020) study the productivity effect in the short run, I am not aware of any work that studies the productivity effect beyond the short run.

Roadmap The rest of the paper is organized as follows. Section 2 discusses the source of my data and how I construct each variable, including monetary policy shocks, financial variables, and innovation measures based on patent applications. Section 3 presents my main results based on aggregate data, while Sections 4 and 5 present my results based on firm-level data.

2 Data

My paper has two goals. First, I want to estimate the influence of an expansionary monetary shock on overall innovation. Second, this study highlights the significance of liquidity in how monetary policy shocks affect innovation. To address these inquiries, I have constructed an innovation measure using patent data.

I constructed the innovation variable for firms using information extracted from patent applications. While acknowledging that patents may not capture all forms of innovation, given the existence of non-patented inventions, they remain a valuable data source for studying innovation due to their inherent association with significant technological advancements. Previous research focusing on the relationship between innovation and monetary policy frequently employs R&D as a measure of innovation. Given the objectives of this paper, several compelling reasons emphasize why a firm's patent applications present an optimal measure of innovation instead of R&D.

Patent data stands out as a relatively dependable source, circumventing the measurement challenges that often hinder the utilization of firm-level R&D data. For instance, employing indicators such as intangible capital (*intanq*) or R&D variables (*xrdq*) from Compustat could be problematic, as they might not faithfully capture firms' innovation endeavors. Over 70% of observations exhibit missing values for R&D variables across the sample period. Addressing this issue of missing values holds paramount importance within the context of this study. Traditional practice treats missing values as zeros, assuming that they signify a lack of innovation activity. Nonetheless, this heuristic approach lacks a micro-founded basis and fails to ensure that the resulting innovation measures are accurate.[5] In addition, Koh and Reeb (2015) emphasize that firms with missing R&D records contribute 14 times more granted patents compared to firms with a recorded R&D of zero. This observation implies that a lack of R&D data does not necessarily equate to a dearth of innovation efforts. Instead, due to the discretionary nature of how expenses are categorized as R&D, managers may opt to not disclose certain expenditures in their financial reports.

Additionally, patents hold a stronger potential for delineating productivity growth than other available measures, since they can serve as a tangible indicator of a firm's innovation activities. This explains why firms' patent applications have been widely embraced as a proxy for successful knowledge capital creation. Furthermore, established causal relationships between a firm's productivity and its patents substantiate the notion that knowledge capital—rather than R&D, an input for innovation—plays a pivotal role in determining productivity.

[5] Peters and Taylor (2017) offers valuable insights for constructing a comprehensive gauge of intangible capital using Compustat. However, this approach also assumes zero R&D for missing values.

2.1 Patent Dataset

Patent dataset is sourced from the U.S. Patent and Trademark Office (USPTO), which maintains records of U.S. patent documents. The USPTO dataset has universal coverage, limiting measurement error. The dataset offers comprehensive details about a patent, including information about the inventor, description, filing date, granted date, and similar aspects. However, a complication arises from the dataset's distinctive firm identifier, posing a challenge to merging it with Compustat data. To address this, I employ crosswalk files from Bena et al. (2017) and Dorn et al. (2020) to enhance data alignment. The USPTO dataset has limited information on patents granted before 1975. To address this, I supplement it with a derived patent dataset from Kogan et al. (2017), which provides more comprehensive pre-1975 data.[6]

2.2 Innovation Metric

With the patent dataset, few methods have been employed to study innovation decisions or their impact. The prevalent approach in the literature is to treat investments as stock variables (Hall, Jaffe, and Trajtenberg, 2005; Lucking, Bloom, and Van Reenen, 2019). Accordingly, I treat patent stocks as my main measure of innovation. I compute each firm's patent stock by considering a quarterly depreciation rate of 4%.[7] Furthermore, prior research has indicated that the quantity of patents may not accurately reflect the extent of a firm's innovativeness. In simpler terms, the basic metric may not reflect the quality of innovation. Hence, I incorporate an additional metric, citation-weighted patents, following the outline provided by Hall, Jaffe, and Trajtenberg (2005) to evaluate the quality of patents based on the number of forward citations they receive. This metric captures the scientific importance of each patent. Scaling is often used to adjust for citation truncation lags as newer patents have had less time to accumulate references. For example, Kogan et al. (2017) construct citation-weighted patents by a given firm f at time t as,

$$\Theta_{f,t}^{cw} = \sum_{j \in P_{f,t}} \left(1 + \frac{C_j}{\bar{C}_j}\right), \tag{1}$$

where $P_{f,t}$ denotes the set of patents issued to firm f at time t and $\bar{C}_j$ is the average number of forward citations received by the patents that were granted in the same year as patent j.

However, since my research centers on investigating how monetary policy influences innovation, this approach could pose a challenge if monetary policy leads to an increase in the number of patent filings, which would likely result in more citations. In such a scenario, the metric may

[6]As an alternative, I reanalyzed the study using patent stock information only from after 1975Q1, revealing no substantial shifts in the primary findings.

[7]Li and Hall (2020) establish industry-specific R&D depreciation rates, although this data pertains only to major U.S. high-tech industries. Here, I adopt the conventional assumption of an annual depreciation rate of 15%, equivalent to 4% per quarter.

not effectively capture the true quality of patents. Consequently, I adopted a different approach outlined by Akcigit et al. (2018) to create a citation-weighted innovation metric.[8] This metric considers the citations accumulated by a particular patent within a three-year period following its priority date, addressing the issue of citation truncation. The primary indicator of knowledge investment becomes the count of citations received by the patent,

$$\Theta_{f,t}^{cw} = \sum_{j \in P_{f,t}} \left(1 + \sum_{\tau=t}^{t+2} C_{j,\tau} \right), \tag{2}$$

where $C_{j,\tau}$ denotes the number of citation that patent j receives at time τ. Using this method minimizes the possibility of monetary policy affecting patent applications within a three-year timeframe, ensuring that the number of citations remains unaffected by monetary policy shocks. As a robustness check, I also consider a different window.

Once the innovation measure is constructed, my focus centers on the timeframe spanning from 1988Q1 to 2011Q4 for the primary analysis.[9] In 1994, the U.S. president endorsed the General Agreement on Tariffs and Trade (GATT), which triggered significant alterations to U.S. patent law starting in 1996. These changes, essential for all patent system participants, encompass adjustments to patent protection durations and the establishment of a domestic priority document, namely the provisional application. I create a time series depicting innovation efforts to assess how this legislation impacted firms' innovation activities. Figure 1 presents the outcomes: the left panel illustrates the evolving proportion of firms initiating new patent applications, while the right panel charts each firm's mean patent count, contingent upon having at least one patent within a specific period. There was a surge in patent applications in 1995, just prior to the law's implementation. Consequently, including data prior to 1995 could conflate the influence of GATT with that of monetary policy shocks, posing a concern. To prevent any potential structural shifts stemming from the implementation of GATT, I limit the sample not to estimate the effect between the period before GATT and after.[10]

Additionally, I confine the sample until 2011 to establish a comprehensive patent dataset. I assume that the date of patent application, rather than the date of patent granting, represents the inception of new technology—a practice commonly adopted in prior research to handle patent data. However, the patent information available from the USPTO pertains solely to granted patents.[11]

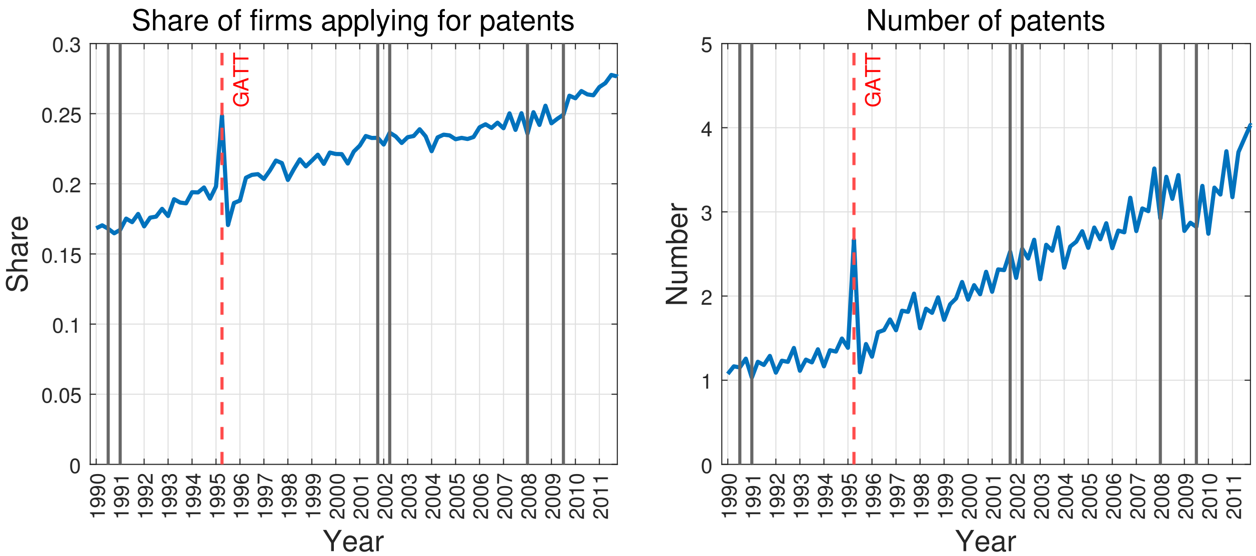
[8] In the citation model presented in Akcigit et al. (2018), they utilize only the summation of $C_{j,\tau}$ from $\tau = t$ to $\tau = t+2$. However, in this study, I introduce an additional factor of 1 to account for the patent itself, aligning it with the approach adopted in Hall, Jaffe, and Trajtenberg (2005).

[9] The sample includes monetary policy shocks until 2007Q4

[10] As a robustness check, I exclude the period before 1995Q2, and this adjustment does not alter the fundamental findings.

[11] In this paper, I only use patents granted to construct innovation metric of individual firm. USPTO also provides information of pre-grant applications. However, since the dataset starts from 2001, it is hard to construct comprehensive firm-level innovation measures including patents yet to be granted.

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 for a single firm.

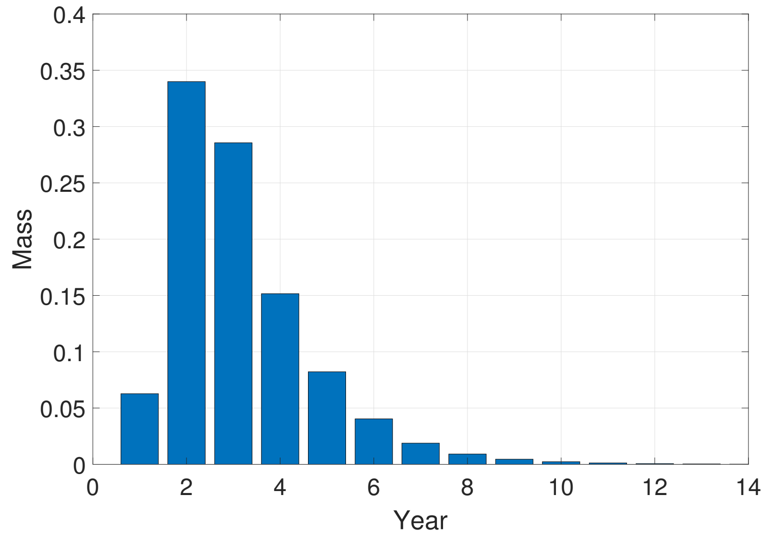
This implies that patents not yet granted are absent from the dataset, irrespective of their filing date. Consequently, technological advancements already made but not yet patented are not reflected in my innovation measure. Therefore, utilizing the entire dataset without any limitations would introduce inaccuracies into the innovation measure. This issue is exacerbated if a considerable duration is needed for new technology to secure USPTO patents.

Figure 2 depicts the distribution of time gaps between the dates of patent application and the dates when they were granted. Consistent with results documented in the literature (Hegde, Herkenhoff, and Zhu, 2023), on average, the time span between application and grant is approximately three years, although it can extend further in some cases. About 99.9% of the sample corresponds to gaps of roughly eleven years. This suggests that patents applied for prior to 2011 should be encompassed in the recently published dataset. By imposing a sample limitation until 2011, I am able to compile a thorough firm-level innovation dataset. As a robustness check, I relax this condition and use more observations, which doesn't change my main results.

2.2.1 Value of patent

This paper also underscores how the price of patent responds to expansionary monetary policy shocks. The dataset from Kogan et al. (2017) is valuable in assessing the economic significance of each patent, as they establish the real value of each patent in dollar terms. To evaluate patent economic worth, they propose an innovative approach employing stock price reactions to patent grant

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.

announcements. The USPTO releases patents on Tuesdays and publishes the *Official Gazette*, detailing newly granted patents along with technical descriptions. This information influences the market, signifying the initial success of an application. Starting on Tuesday (the official announcement day), they gauge total market capitalization changes until Thursday (a 3-day window). After adjusting for aggregate market movements and idiosyncratic stock return volatility, this series offers insight into the economic value of innovation for shareholders. I have summarized their methodology for deriving patent values in Appendix B.

2.2.2 Characteristics of Innovation Metric

Table 1 shows the descriptive statistics on the unbalanced panel from my final dataset. This is taken from an underlying firm level panel which remains after matching the balance sheet data and innovation data. Innovation metrics are constructed based on the perpetual inventory method using the number of patents and citations. While I mainly use the economic value of patents to gauge the effect of monetary policy shocks on the price of new technology, I also construct innovation metric based on economic values of patents as a robustness check.[12] The patenting count is highly skewed and the innovation metrics are correlated with each other.

[12] The dataset from Kogan et al. (2017) only includes patent information for firms with stock market information. As a result, the sample I use in my primary analysis, which investigates the impact of monetary policy on firms' innovation based on patent counts, covers a broader range of patent data. Nevertheless, the findings in this paper remain consistent even when utilizing the dataset from Kogan et al. (2017).

Table 1: Summary statistics of innovation metrics

	A. Distribution			
	Input	Output (Patent)		
	R&D	Number of patents	3-years citations	Economic values
Mean	277.7	40.4	134.5	559.2
Median	20.0	1.3	3.0	0.0
Standard deviation	1683.5	357.0	1310.7	6738.2
Observations	543,732			

	B. Correlation			
	R&D	Number of patents	3-years citations	Economic values
R&D	1.00			
Number of patents	0.69	1.00		
	(0.00)			
3-years citations	0.68	0.95	1.00	
	(0.00)	(0.00)		
Economic values	0.83	0.64	0.65	1.00
	(0.00)	(0.00)	(0.00)	

Notes: Summary statistics of innovation metrics in the data. All output variables are considered as stock variables, calculated using the perpetual inventory method with a quarterly depreciation rate of 4%. R&D is sourced from the NIPA Tables, measured in millions of dollars, and adjusted for inflation using the 1982-based deflator. The count of patents is determined by the number of patent applications. The calculation of 3-year citations is based on Equation 2. Economic values of innovation is sourced from Kogan et al. (2017), measured in millions of dollars, and adjusted for inflation using the 1982-based deflator.

2.3 Other data

To uncover the fundamental channels through which monetary policy affects innovation, I integrate multiple additional datasets that provide evidence from various perspectives.

2.3.1 Monetary policy shocks

To study the effect of monetary policy on innovation, it is essential to identify exogenous changes in monetary policy. 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 changes in the policy rate driven by changes in macroeconomic conditions. Since Kuttner (2001), many attempts have been made using the change in the federal fund future to construct monetary policy surprises. In this paper, I use surprises from Bauer and

Swanson (2022) as a measure of monetary policy shocks. With a sample period that runs from 1988Q1 to 2007Q4, the series has an average -1 basis point change, with a standard deviation of 8 basis points at the quarterly level.[13] Additionally, I use shock series from Gertler and Karadi (2015), Gorodnichenko and Weber (2016), and Barakchian and Crowe (2013). Table 2 provides basic summary statistics of monetary policy shocks that I use in the final data sets.

Table 2: Summary statistics of monetary policy shock

	Bauer and Swanson	Gorodnichenko and Weber	Gertler and Karadi	Barakchian and Crowe
Mean	-0.008	-0.045	-0.045	-0.139
Median	-0.003	-0.013	-0.009	0.164
Standard deviation	0.076	0.103	0.110	1.249
Min	-0.239	-0.428	-0.546	-5.159
Max	0.195	0.237	0.170	2.934
Observations	80	72	72	77

Notes: Summary statistics of monetary policy shock used in the analysis. The sample period starts from 1988Q1 and 2007Q4.

2.3.2 Balance sheet data

To construct firm-level data, I use the Compustat and the WorldScope Database at the Wharton Research Data service (WRDS).[14] Both sources provide detailed balance sheet information for publicly listed U.S. incorporated firms covering the period from 1988Q1 to 2011Q4.

Utilizing balance sheet data from WRDS offers several advantages, primarily its ability to provide insights into various firm attributes on a quarterly basis. This high-frequency characteristic is especially advantageous for estimating the effect of monetary policy shocks on firms' decisions. The comprehensive data on firms' financial standings allows me to disentangle the influence of liquidity from other observable features of these firms. In the main specification, I exercise control over all variables previously established in existing literature to determine responses in tangible capital following monetary shocks. This measure minimizes the potential for errors stemming from 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. This comprehensive control allows for a precise examination of the transmission mechanism of monetary

[13]As a starting point, I take the period prior to the Great Recession as a reference. However, to increase the sample size, I take two additional steps. First, I incorporate data from the period following the Great Recession, which doesn't significantly alter my estimates. Second, I convert the dataset into a monthly format, allowing for a larger number of observations and a more detailed examination of how overall innovation responds to shocks. Among all the aggregate variables, it's worth noting that only patent filings can be constructed at the monthly level. Importantly, the primary result remains unchanged.

[14]The WorldScope Database is used to construct firms' age in the firm-level analysis.

policy on innovation, uncovering the primary drivers of heterogeneity in innovation responses contingent upon monetary policy shocks. To mitigate the impact of outliers, each firm-level variable is subjected to a 0.5% winsorization. Detailed information regarding the development of individual firm-level variables is included in the Appendix B. However, it's important to note that a limitation arises from using Compustat's balance sheet data, as it solely encompasses publicly listed U.S. firms, thus excluding private enterprises absent from the stock market.

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 1988Q1 to 2011Q4, while the monetary policy shock is from 1988Q1 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, enabling me to accurately estimate the coefficient of interest over the longer horizon.[15] The sample only includes firms incorporated in the US and excludes firms in the financial industry or utilities.

3 Aggregate Analysis

In this section, I conduct an aggregate analysis and emphasize the role of innovation in comprehending the enduring impact of monetary policy shocks on productivity. I present findings indicating that an expansionary monetary policy shock leads to heightened patent values, increased aggregate patent applications, and higher TFP. These observations suggest that innovation could serve as a channel through which monetary policy shocks influence TFP outcomes, extending beyond immediate effects.

3.1 The Effects of Monetary Policy Shocks on Innovation

The main specification in this section is based on Jordà (2005) local projection,

$$\log(y_{t+h}) - \log(y_{t-1}) = c^h + \sum_{j=1}^{J} \alpha_j^h \left(\log(y_{t-j}) - \log(y_{t-j-1})\right) + \sum_{i=0}^{l} \beta_i^h \varepsilon_{t-i}^m + X_t + f_{t+h|t-1}, \quad (3)$$

where $h \geq 0$ denotes the horizon; y_t is the variable of interest, and ε_t^m denotes the monetary policy shock I discussed in Section 2. The coefficient of interest is β_i^h for $h = 0, ..., 28$, 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 my main analysis, I include eight lags of the shocks and four lags of the quarterly aggregate innovation growth rate. X_t is a vector with four lags of GDP growth, the

[15] I also verify the primary results using monetary policy shocks up to the fourth quarter of 2011, and this adjustment does not alter the primary findings.

inflation rate, and the unemployment rate, in line with previous research (Ottonello and Winberry, 2020). The standard errors are computed following the methodology in Driscoll and Kraay (1998), which accommodates for varied serial and cross-sectional patterns across different time horizons. For each impulse response, I used a 68% and a 90% confidence interval.

3.1.1 Results

The results are plotted in Figure 3. To facilitate interpretation, I made several adjustments. First, I multiplied the dependent variable, denoted as $(\log(y_{t+h}) - \log(y_{t-1}))$, by 100. Second, I standardized and normalized the sign of the monetary policy shock, ε_t^m, so that a positive value corresponds to an expansionary monetary policy shock. One standard deviation of a monetary policy shock equates to an 8 basis point change in the federal funds rate. The impulse response function displayed in Figure 3 illustrates how each macroeconomic variable reacts to a one standard deviation expansionary monetary policy shock.

As a gauge for U.S. productivity, I rely on the quarterly, utilization-adjusted TFP series outlined by Fernald (2014). The lower left panel of Figure 3 illustrates the computed impulse response of TFP based on specification 3. Aggregate TFP displays growth and maintains its effect well beyond the short-term. A one standard deviation expansionary monetary policy shock induces a 1.5% TFP increase.[16]

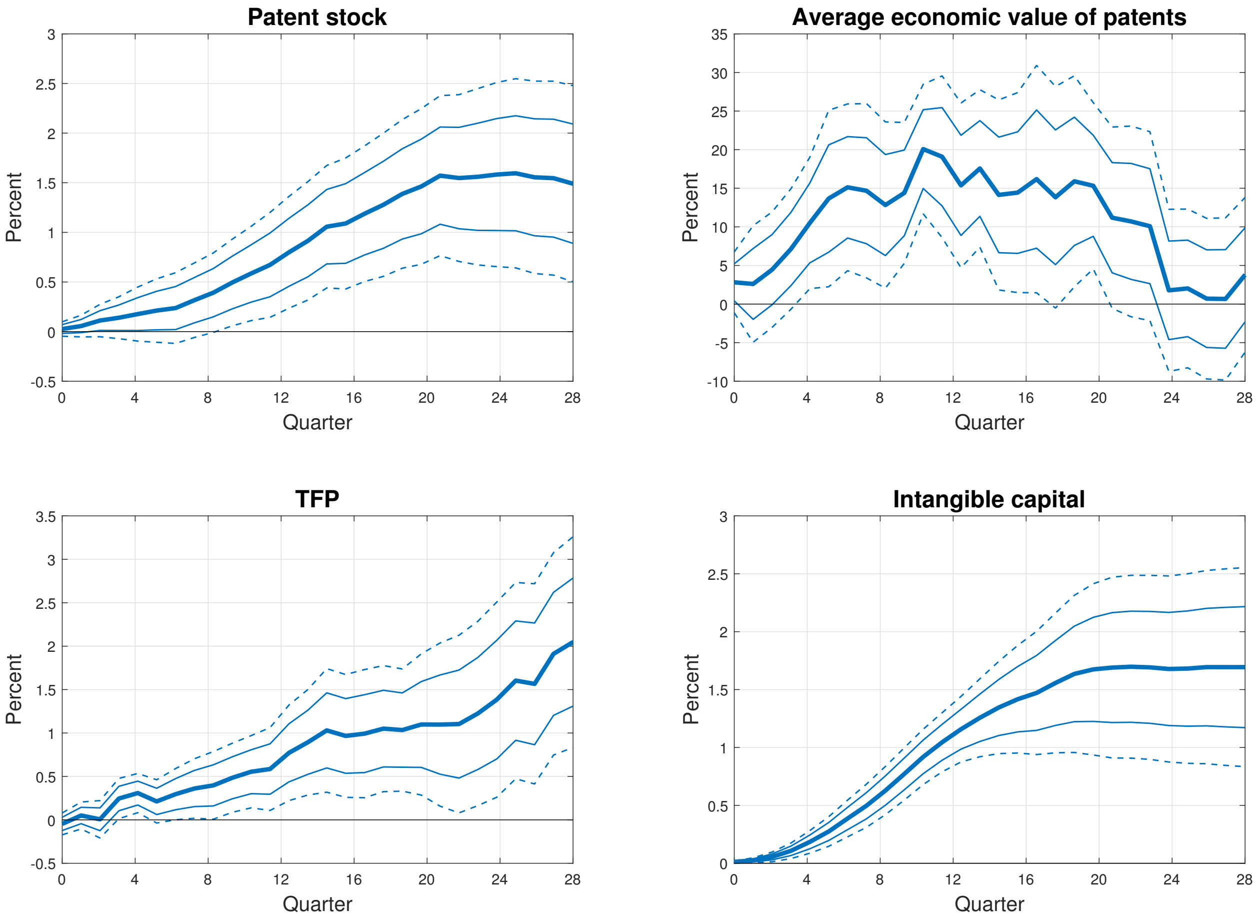
To gauge the impact of expansionary monetary shocks on innovation, as measured by patent applications, I construct a time-series dataset of the mean number of patents held by each firm during a given period from the patent data.[17] The upper left panel in Figure 3 depicts the response of the aggregate patent stock. This stock exhibits gradual growth and peaks at approximately 1.5% roughly six years after a one standard deviation expansionary monetary policy shock, and then begins to decrease.[18] This response becomes statistically significant two years after the shock. This timing aligns with reason, since knowledge capital take longer to materialize than tangible capital.

[16] Meier and Reinelt (2020) highlights that a one standard deviation contractionary shock reduces TFP by 0.5% three years after the shock, where one standard deviation equals to 4 basis points.

[17] The analyzed sample encompasses firms listed in the Compustat data. To convert firm-level innovation metrics into aggregate-level, I construct the stock of knowledge capital using the average quarterly growth rate of knowledge capital stock. I create the knowledge capital stock by calculating the average quarterly growth rate of knowledge capital. Initially, I calculate the average innovation metric across firms within the sample during the first quarter of 1988Q1, and then I utilize the average growth rate for each subsequent quarter to generate the time-series data for innovation metrics. I assume that when a firm exits the market, its associated technology vanishes. The resulting dataset is derived from patents listed in Compustat, with the omission of companies that exit during the same period. As an alternative approach, I develop a version of the series that assumes patent depreciation even after firms exit the market. However, this adjustment does not substantially alter the core outcomes—namely, the expansionary shock leads to heightened aggregate innovation.

[18] While the dataset has a limited number of observations, it's noteworthy that the cumulative impact of monetary policy shocks on innovation, which stood at 1.5 percent at 24 quarters, exhibits a decrease to 1.2 percent at the 32-quarter mark, signifying a decline in magnitude.

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



Notes: This figure displays the impulse responses of aggregates to a negative, one standard deviation monetary policy shock using specification 3. Quarterly TFP is from Fernald (2014), and monetary policy shock is from Bauer and Swanson (2022). The sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

To explore how the shock influences the responses of intangible investment, I utilize data from the National Income and Product Accounts (NIPA) Tables, sourced from the U.S. Bureau of Economic Analysis (BEA). Specifically, I focus exclusively on R&D to compose firms' intangible capital stock. The impulse response function for this newly constructed variable is depicted in the lower right panel. Following a one standard deviation expansionary shock, intangible capital increases by 1.5% after four years. The observed behaviors of patent stock and intangible capital suggest that it takes approximately two years for investments to materialize. To further support this argument, I illustrate the correlation between patent applications at time t and intangible capital at time $t-i$, on an annual basis, where $i = -3, \ldots, 3$. This is presented in Figure A.22. The chart demonstrates that innovation during period t displays correlation with investment from the past two years. This observation explains the temporal gap between the initiation of intangible capital's response and the onset of the initial response seen in patent stock.

This paper aligns with existing literature by examining the mechanics behind the productivity effects of monetary policy shocks. However, my focus extends to medium- and long-term effects. To address medium-term productivity effects, I extend my analysis horizon to seven years. Additionally, I delve into the relationship between changes in patent stock and TFP, as detailed in the Appendix A.3. Figure A.21 demonstrates that a 1 percentage point shift in the patent stock leads to a 3% adjustment. This accentuates the notion that fluctuations in aggregate innovation could be the primary driver of conditional productivity growth arising from monetary policy shocks.[19]

To justify this substantial and persistent impact on aggregate innovation, I offer a rationale rooted in the appreciation of patent value following the shock, which in turn encourages firms to invest in intangible capital. A common approach to gauging a patent's importance is through citation-weighted patents, reflecting the scientific contribution of a new invention. However, scientific importance doesn't always align with economic value, so employing the number of citations to estimate the influence of a monetary shock on patent valuation might not be pertinent.

I address this issue by adopting the recently developed method by Kogan et al. (2017), which evaluates patents based on market reactions to patent grant news. This approach facilitates the creation of a time series illustrating the average economic value of newly granted patents within each period. This measure can be interpreted as the market's perception of the total potential payoff for each patent at the time of its announcement, representing a firm's perception of the profitability tied to owning a new technology. As illustrated in the top right panel, the expansionary monetary policy shock significantly bolsters the average patent value. About three years after the shock, its estimated effect on the average patent value is approximately 15%. This estimated impact surpasses those reported in previous literature. Moran and Queralto (2018), for instance, outlines that a 60 basis point expansionary monetary policy shock can augment the value of new technology by 2%, as per their theoretical model. This notable surge in patent value elucidates why an expansionary monetary policy shock motivates firms to allocate more resources towards intangible capital.

3.1.2 Robustness

I conduct various sensitivity tests to examine the robustness of main findings. I report detailed results in Appendix A.2

First, I investigate whether the core findings were influenced by the choice of innovation metric. My initial measure was based on the count of patents. I examine if the results remained consistent

[19]Comin and Gertler (2006) and Meier and Reinelt (2020) highlight the significant delay between an invention and its practical implementation, typically spanning approximately five years. From Figure A.21, it is evident that patent filings result in an uptick in TFP after a three-year interval.

when using a citation-weighted metric derived from specification 1 or 2. I performed an additional test to assess the null hypothesis that monetary policy shocks do not affect an innovation metric based on economic value. The point estimates indicate that expansionary monetary policy shocks lead to increased innovation, although the estimates are somewhat noisy. Nevertheless, the results support the rejection of the null hypothesis of no response in innovation when analyzed collectively across all time horizons (with p-values < 0.01).

As a second set of robustness checks, I check that my results held up when different control variables other than innovation metrics are used. I started by considering different monetary policy shocks. Apart from the surprises provided by Gertler and Karadi (2015), I also utilized shocks constructed by Gorodnichenko and Weber (2016) and Barakchian and Crowe (2013). These alternative shocks produce qualitatively similar estimates. Furthermore, I explore the impact of altering the lag length in the specification 3. Changing the number of lags for monetary policy shocks had minimal qualitative impact on the results.

Finally, I check other possibility that might changes the sample. First, when constructing the patent stock, I incorporated the assumption that patents continue to depreciate even after companies exit the market. This modification does not significantly change the fundamental findings, which are that an expansionary shock results in increased overall innovation. In addition, I assess the robustness of my results by examining changes in the sample period. I extend my analysis to include shocks until the end of the sample period (2011Q4), which encompassed the Great Recession. Moreover, I exclude the period before GATT to ensure that structural change does not affect my results.

3.2 Why does the average economic value of patents increase?

The evidence from Section 3.1 suggests that expansionary monetary policy shocks encourage firms to invest more in knowledge capital by increasing the future value of technology. This section investigates the underlying channel through which monetary policy enhances the average economic value of innovation. As mentioned earlier, the average economic value was calculated based on fluctuations in the stock market. This implies that the average economic value reflects shareholders' expectations. The price of a patent, which is the average economic value in this paper, will be determined by the present value of all future dividends generated by the innovation,

$$P_t = \mathbb{E}_t \left\{ \sum_{i=1}^{\infty} \frac{D_{t+i}}{(1+r)^i} \right\},$$

where P_t is the price of innovation at time t, D_t is the dividend from the innovation, and r is a real interest rate. Specifically, D_t is the function of quality of innovation and aggregate demand,

$$D_t = f(\text{quality of innovation, aggregate demand}),$$

This implies that there are three ways for the value of innovation to rise. First, if firms invent new technology with better quality. Second, even if the technology is the same, the price may rise if there is a cyclical upswing. Lastly, a shift in the discount rate after expansionary monetary policy shocks can also be a source of fluctuation in the price of the new patent. To investigate which forces drives the responses, I construct the average number of citation of each patent as I discussed in Section 2 which would capture the quality of innovation (Akcigit et al., 2018). Figure 4 shows the impulse response of the average quality of patent conditional on monetary policy shocks. The average quality of patents decreases and the effect persists. This pattern highlights two important points about how innovation responds to monetary policy shocks. First, expansionary monetary policy may misallocate resources, and aggregate innovation is driven by changes in the number of technology rather than the quality of technology. Lowering interest rates could incentivize low-productivity firms to invest more, resulting in increased resource allocation to them.[20] Consequently, a low interest rate may lead to inefficient resource distribution among diverse firms. This implies that the aggregate innovation response is driven by quantity rather than quality.

Second, given the substantial fluctuations in the average economic value of patents in response to monetary policy shocks, it implies that the increase in the average economic value of innovation resulting from expansionary monetary policy is not attributed to innovators creating higher-quality technology. This confirms that the average economic value of patents rises due to changes in the discount factor and cyclical upswing following expansionary monetary policy shocks.

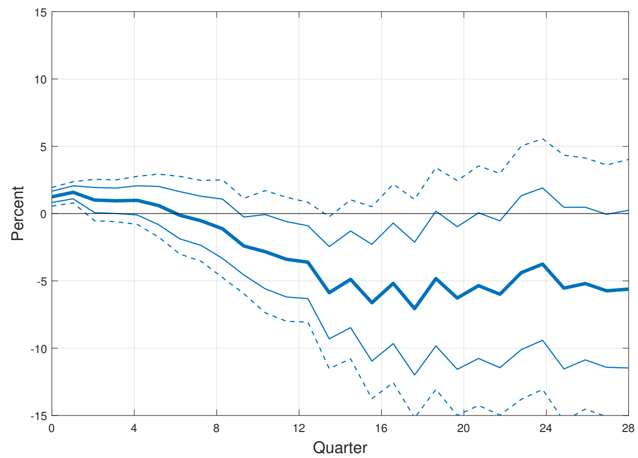
3.3 How Important is the contribution of monetary policy shocks to Innovation?

I've demonstrated that monetary policy shocks enhance the value of innovation. The next question is whether this impact is economically substantial. In this section, my aim is to underscore the importance of monetary policy shocks in comprehending variations in innovation. I quantify the contribution of monetary policy shocks to innovation, employing the forecast error variance decomposition (FEVD), which helps us determine the portion of innovation's variability that can be attributed to monetary policy shocks during a specific time period.

Within the framework of local projections, I follow the method proposed by Gorodnichenko and Lee (2020). The procedure consists in two steps: first, I estimate forecast errors $\hat{f}_{t+h|t-1}$ for a given time horizon h using specification 3. Next, I conduct a regression analysis using these estimated forecast errors and the shocks that occurred between t and $t+h$, as follows:

[20] Hori (2020) shows this response after monetary policy shocks using a theoretical model.

Figure 4: Impulse responses of the average quality of innovation to expansionary monetary policy shock



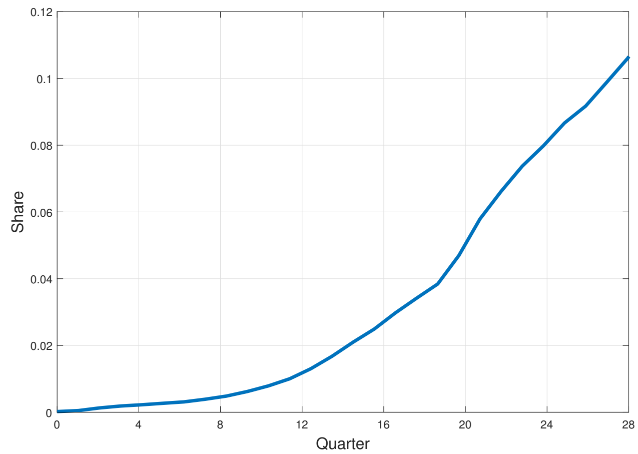
Notes: This figure displays the impulse responses of the average scientific importance to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time. The quality of patents is determined by the number of citations they receive within three years after being filed.

$$\hat{f}_{t+h|t-1} = \alpha_{\varepsilon^m,0}\varepsilon^m_{t+h} + \cdots + \alpha_{\varepsilon^m,h}\varepsilon^m_t + \tilde{v}_{t+h|t-1},$$

The R^2 of this regression measures the share of the forecast error variance explained by the shock at horizon h. This approach offers a means to gauge the degree to which monetary policy shocks significantly influence the dynamics of innovation. Figure 5 illustrates the estimates obtained through variance decomposition. In the short term, monetary policy shocks make a relatively minor quantitative contribution to innovation. This is unsurprising as monetary policy is less likely to have an immediate impact on innovation, typically accounting for less than 1% of the variation in innovation until two years after the shock. However, monetary policy shocks become more significant over time. Approximately 12% of the forecast error variance is attributed to monetary policy shocks seven years after the initial shock. This outcome underscores the pivotal role that monetary policy plays in explaining fluctuations in innovation within the United States.

In addition to FEVD method, I use, as a reference point, a comparison between the estimated effect of a monetary policy shock on innovation and its effect on tangible capital in Figure A.23. Four years after a one standard deviation expansionary monetary policy shock, tangible capital increases by 3%. This observation suggests that the influence of the shock on innovation is significant, since it is comparable in size to the responses observed in tangible investments, and this effect seems to persist over time. Moreover, the average quarterly change of my innovation metric is around 1.8%, which suggests that the effect of monetary policy shocks on innovation is econom-

Figure 5: Contribution of monetary policy shocks to forecast error variance of innovation



Notes: This figure displays how monetary policy shocks contribute to the error variance in forecasting the aggregate innovation metric.

ically sizable.

4 Firm-level Analysis

I present evidence at the firm level to delve into the mechanism that drives the impact of monetary policy shocks on firms' innovation. To be specific, I focus on the significance of firm-specific attributes in comprehending diverse responses to innovation. This will elucidate the key factors that have a significant impact on the transmission of monetary policy to overall innovation.

4.1 Heterogeneous Innovation Responses

In this subsection, the main goal of my analysis is to see which firms are the most responsive to monetary shocks. Aggregate evidence emphasizes the role of innovation in explaining the productivity effect of monetary policy shocks. I now explore which firms are the most responsive in innovation, which will clarify the underlying mechanism. 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 3 provides the summary statistics of the dependent variables used in my analysis. In each quarter, approximately 23% of all firms file at least one patent, and approximately 52% of

Table 3: 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	0.001	2.04	0.213	0.519	0.166
Median	0.000	0.00			0.074
Standard deviation	0.520	19.73			0.207
Observations		567,760			

Notes: Summary statistics of firm-level variables computed over all firm-quarters observations starting from 1988Q1 to 2011Q4. $\Delta_1 \log(\text{Innovation}_{i,t})$ 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.

firms have filed at least once throughout the sample period.[21]

This is the first paper to estimate the semi-elasticity of innovation with respect to monetary policy shocks depending on firms' financial position. I incorporate all firm control variables previously employed in prior research that examined heterogeneous responses of tangible capital investment to monetary policy shocks into my regression analysis. I also include each interaction term between firm characteristics and monetary policy shocks within the same estimation equation. This approach aims to prevent any omitted firm attributes from explaining the central outcomes. The fundamental specification is

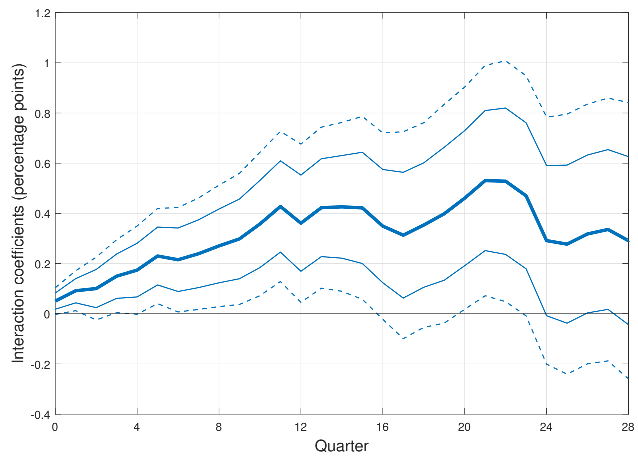
$$\Delta_h \log\left(\text{Innovation}_{j,t+h}\right) = \alpha_j + \alpha_{st} + \left(\Theta_h' + \varepsilon_t^m \Omega_h'\right) W_{jt-1} + u_{j,t+h}, \tag{4}$$

where $h = 0, 1, \ldots, 28$ 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 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 at the SIC 1-digit level. ε_t^m is the monetary policy shock. W_{jt-1} is 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. $u_{j,t+h}$ is a residual. I 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. 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. This term estimates how firms' innovation changes over time depending on their characteristics after monetary policy shocks.

[21] To address the issue that not all companies engage in patent filings, I examined whether my primary results are the same when I only consider firms that filed at least one patent during the sample period. This restriction did not significantly alter my outcomes.

To interpret the results easily, I make the same adjustments as in Section 3. A 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 a one standard deviation expansionary shock. In this paper, I mostly focus on liquidity because liquidity has a much stronger impact than any other firm controls.

Figure 6: Heterogeneous response of innovation to monetary policy shocks



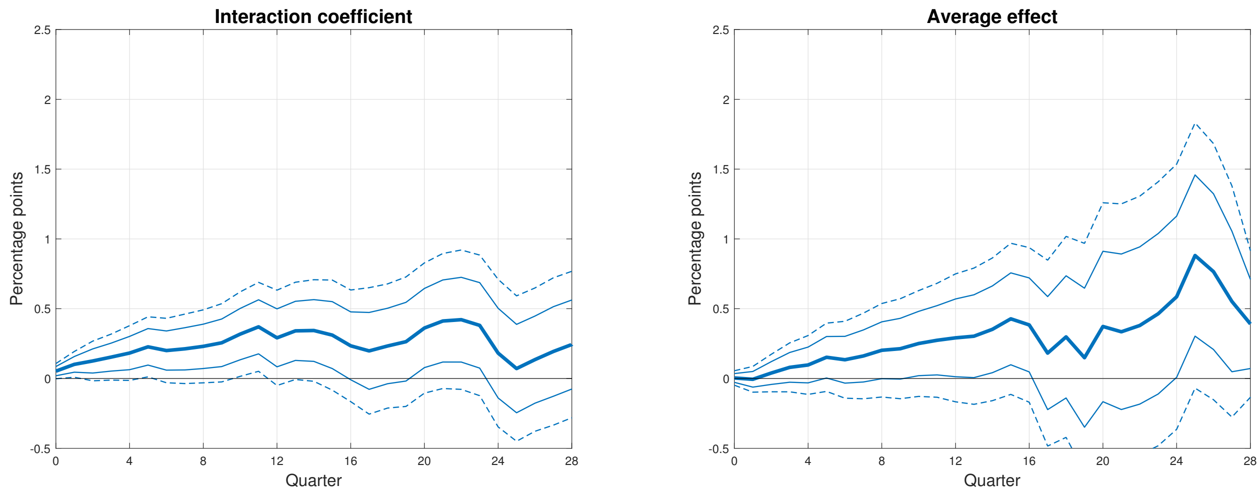
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4. The innovation metric is measured using the number of patent filings. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

4.1.1 Results

Figure 6 displays my individual firm results. The findings reveal a significant role of liquidity, both in terms of its magnitude and the associated confidence interval, in determining the dispersion in innovation responses to monetary policy shock. After a one standard deviation expansionary shock, one standard deviation more of liquidity leads to roughly 0.6 percentage points more innovation. The peak of the differences in liquidity occurs after 5 years.

The point estimates in the figure are statistically significant. To assess their economic significance, I initially examine the distribution of patent applications. Overall, the distribution is skewed, with a median growth rate of 0% and a mean growth rate of 2.1%. The heterogeneity associated with liquidity levels, amounting to 0.6, is not only statistically significant but also holds economic importance. An alternative method to assess the economic significance of this effect involves comparing the coefficient of an interaction term with the main effect, following the approach of Ottonello and Winberry (2020). However, estimating the impact of a monetary policy shock on innovation in the main specification is infeasible due to the sector-by-time fixed effects. Consequently, I relax specification 4 by excluding sector-by-time fixed effects. Instead, I incorporate a sector-by-seasonal-quarter effect and a macroeconomic control vector, encompassing lagged GDP growth, inflation rate, and unemployment rate, as proposed by Ottonello and Winberry (2020). The outcome is presented in Figure 7.

Figure 7: Heterogeneous response with average effects



Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using specification 4. However, I exclude 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 the monetary policy shock. The right panel plots the main effect of the monetary policy shock, the coefficient on ε_t^m. The innovation metric is measured using the number of patent filings. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

The coefficient of the monetary policy shock can be interpreted as the effect of a monetary policy shock on innovation in firms with zero cash holdings. Adding the main effect does not significantly change my main findings: expansionary monetary policy shocks stimulate innovation in firms with high liquidity. The effect of the interaction term is comparable to the main effect. This again confirms that the coefficient of the interaction term is economically significant.

4.1.2 Robustness

The observation that the elasticity of innovation in response to an expansionary monetary policy shock increases with the level of liquidity remains consistent even when employing different measures of the monetary policy shock. I test the robustness by changing the definition of innovation metric, shock measures, and sample period. The results are in Appendix A.2.

Despite the acknowledged limitations in the reliability of R&D spending data from Compustat, I incorporate the R&D expenditures for each firm to formulate intangible capital estimates. An issue encountered when transforming a series of R&D flow variables into an intangible capital stock is the absence of information about the initial stock level. I address this challenge by assuming that the initial intangible stock in the first firm-quarter observation is equivalent to the R&D expenditures divided by the sum of the depreciation rate and an annual growth rate of 8%, as indicated by the pre-sample growth rate of new R&D expenditures, following the approach outlined in Hall (1990).

Following Ottonello and Winberry (2020), instead of using $W_{i,t-1}$ in the specification 4, I use $(W_{i,t-1} - \mathbb{E}_i[W_{i,t}])$, which is financial variables after demeaning. By demeaning financial position within firms, estimates are driven by how a given firm responds to monetary policy when it has higher or lower liquidity. This excludes the situation where the results are driven by permanent heterogeneity in responsiveness across firms.

One issue with specification 4 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 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 came from the high-liquidity group after the shock, while there was no response in the low-liquidity group.

5 Why does a firm with liquidity innovate more after expansionary monetary policy shocks?

Drawing from the insights presented in Section 3 and Section 4, I demonstrate that expansionary monetary policy shocks lead to an increase in overall innovation, and firms exhibiting high levels of liquidity exhibit the most pronounced responsiveness to such shocks. However, the precise driving force behind the diversity of responses remains unclear. This variation could arise from a variety of factors. First, I consider the asset price channel. If patents held by high-liquidity firms experience greater appreciation compared to those held by low-liquidity firms, this could potentially result in heterogeneous innovation responses. Second, I examine the financing channel. If the expense associated with financing innovations is lower for high-liquidity firms, this might also lead to heterogeneity. Both scenarios could propel innovation more significantly for firms with ample liquidity than for their counterparts.

In this section, I present evidence to argue that the asset price channel cannot account for the observed heterogeneity, while financing channel is crucial for understanding the variations in reactions. Moreover, I illustrate that high-liquidity firms have an advantage in financing their intangible investments. This advantage doesn't stem from their superior position in the credit market due to their liquidity but rather from their ability to readily tap into their accumulated cash reserves to meet the adjustment costs associated with the investment.

5.1 Asset price channel

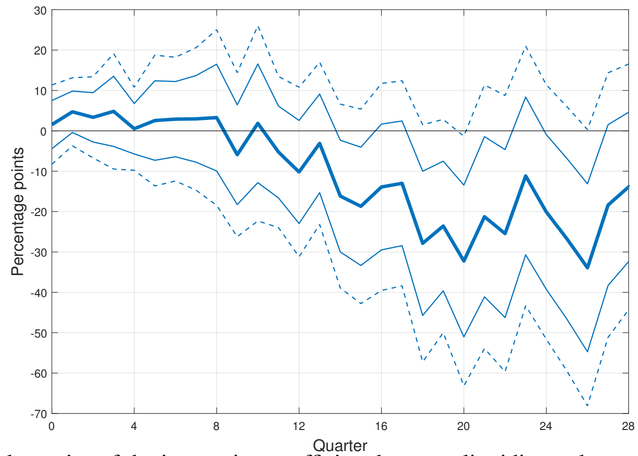
The asset price channel underscores the close relationship between monetary policy and financial markets. Monetary policy, by increasing asset prices and wealth, can spur economic activity. In the context of this study, patents are considered a type of asset, and this channel may result in varying effects on different firms. Additionally, since this paper evaluates the value of innovation based on stock market performance, exploring this aspect is a valuable pursuit. 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 firm's liquidity. The question is straightforward. Do patents of high-liquidity firms appreciate more after expansionary monetary policy shocks? I use the value of patents from Kogan et al. (2017) to test this hypothesis. I adopt the framework outlined in specification 4, with a modification in the dependent variable to capture the average economic value of new patents held by each individual firm. In certain instances, firms may patent multiple new technologies during a given quarter t. To account for this, I compute the mean economic value of the new patents for each firm. Once this dependent variable is constructed, I proceed with the estimation using specification 4. For the analysis, I restrict the sample to instances where a firm has applied for at least one patent in both periods $t+h$ and $t-1$. I enforce this criterion due to the infrequent nature of new patent applications, often leading to a situation where x_t equals zero for a significant portion of observations. Given that my focus is on discerning variations in valuation post-shock, it is justifiable to exclude firm-quarter observations without patent applications.

Figure 8 plots the dynamics of the interaction coefficient between firms' liquidity and monetary shocks over time. The figure shows that there is heterogeneity in the valuation of patents–firms with low liquidity benefit from expansionary monetary policy shocks in that their patent value appreciated more after the shock. This suggests that the variation in innovation reactions following the shock can be attributed to differences in financing, particularly benefiting firms with limited liquidity as they gain from the increased economic value of innovation.

5.2 Financing channel

The evidence presented above has indicated that the diversity in innovation responses following monetary policy shocks likely arises from cost-related factors. In this section, I will emphasize the costs associated with innovation, particularly the cost of financing. I will do this by presenting empirical evidence that demonstrates how firms fund their innovation, highlighting it as the mechanism through which expansionary shocks contribute to the variance in innovation responses.

Figure 8: Heterogeneous response of patent value to monetary shocks



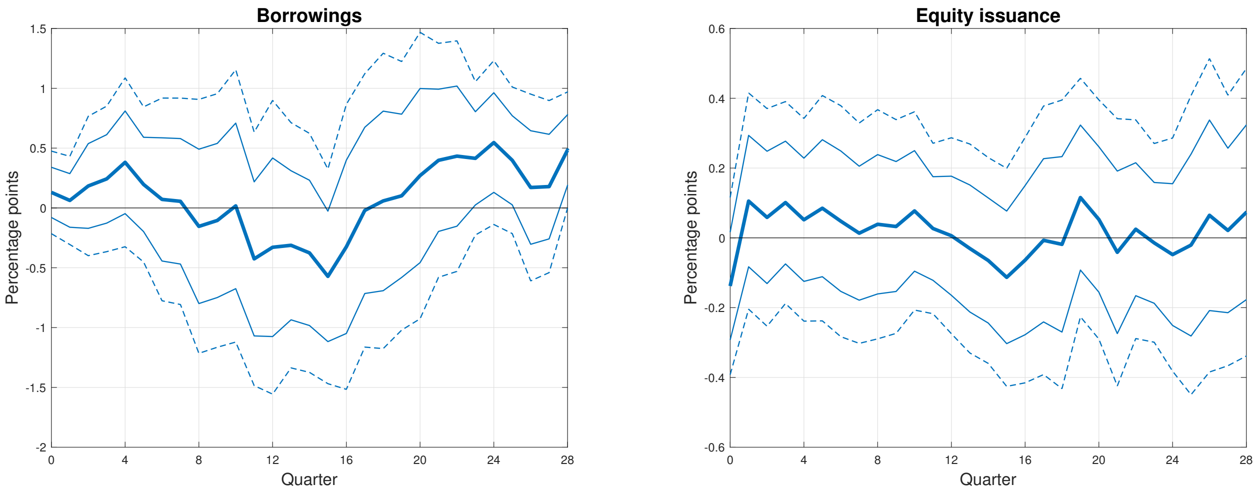
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using specification 4. The log difference of the average economic value of patent is a dependent variable. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

What force drives heterogeneity in financing methods among firms? Faced with unexpected circumstances, firms have two options to finance their investments: utilizing existing cash reserves or resorting to leverage. This involves two key factors: first, firms with ample liquidity might easily secure more borrowing, and second, they might invest directly using their cash reserves. In this subsection, I will argue that the volume of cash reserves is the source of financing heterogeneity following an expansionary monetary policy shock, since it allows firms to invest directly from their cash reserves.

5.2.1 Does a firm with liquidity borrow more?

As a first step, I use firms' borrowing data and see how these change after the shock. I use specification 4, the exact specification that was used in the main analysis. Instead of using innovation measures as a dependent variable, I use the log difference of the debt amount. Aside from borrowing, I also check whether the firms with high liquidity can raise their investment through equity financing. While equity financing differs from traditional credit in that it doesn't involve borrowing money, it is still an important aspect of a firm's financial strategy and can be influenced by changes in monetary policy, particularly through interest rate dynamics and overall credit market conditions. Therefore, it can be considered a part of the credit channel through which monetary policy impacts the broader economy. Previous literature have shown that equity financing is more expensive than internal financing (Hennessy and Whited, 2007; Hall and Lerner, 2010). However, recent literature have found that stock issues are the main marginal source of R&D finance for many firms, especially young firms (Müller and Zimmermann, 2009; Brown, Martinsson, and Petersen, 2012).[22] Under this setting, Ω_h' from specification 4 now captures whether liquidity increases the total borrowing amount after the expansionary monetary policy shock.

Figure 9: Dynamics of the differential response of borrowings to monetary shocks



Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using specification 4. The left panel uses the log difference of real debt amount, while the right panel uses the log difference of the total amount of equity issuance as a dependent variable. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure 9 presents the results. No matter which dependent variables are used, there is no heterogeneity in firms' borrowing activities depending on liquidity levels, which leads to the conclusion that the firms' borrowing decisions are not affected by liquidity levels.

One limitation of my analysis is that I cannot identify the borrowing that is used for intangible capital, since Compustat only provides total amount of debt and equity issuance. However, 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. Several notable characteristics that distinguish intangible from tangible investment: information asymmetry between innovator and debtor and lack of collateral value and etc. 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.[23] Moreover, the low collateral

[22]As the variable from Compustat is flow instead of stock, I used Net cash raised from stock issues (external equity) in period t normalized by beginning of the period book value of total assets (AT). Net cash raised from stock issues is defined as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTK).

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

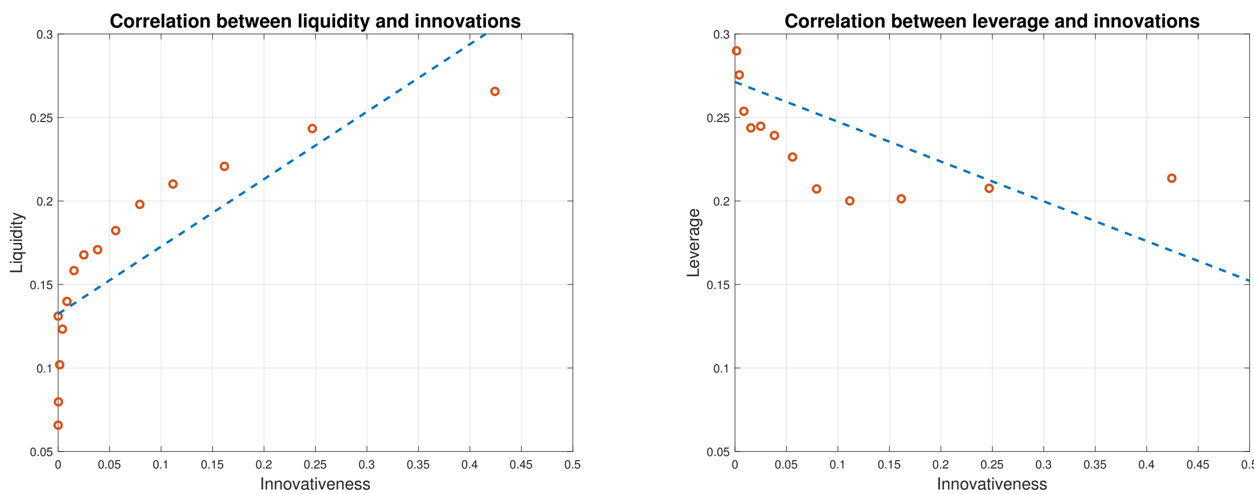
value of intangible capital leads to insufficient lending.[24] On top of that, intangible capital is difficult to finance in the free marketplace given its low redeployability, non-exclusiveness, and low liquidity, which makes acquiring new debt or equity financing more expensive for R&D compared to traditional investments.[25]

Consequently, this suggests that the credit channel is less likely to account for why companies with high liquidity exhibit greater innovation than their counterparts when an expansionary monetary policy shock takes place.

5.2.2 Does a firm with liquidity pay investment adjustment costs easily?

Since the heterogeneity in financing costs is unlikely to be solely attributed to firms' borrowing choices, this implies that the variation in innovation responses is linked to the fact that firms with ample liquidity can readily tap into their accumulated cash reserves to fund their new intangible investments, aligning with findings in the literature.

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



Notes: This figure plots the correlation between firm characteristics and innovation using the binned scatter plot with a fitted line. The last bin is dropped. The left panel shows the correlation between liquidity and innovation, and the right panel shows the correlation between leverage and innovation. The innovativeness of firms is measured with patent stock divided by firms' total assets for normalization.

Figure 10 plots the correlation between firm characteristics and innovation using the binned scatter with a fitted line. Firms are categorized into 25 groups based on their patent stock, and the average liquidity of each group is computed. To avoid the influence of larger firms having more patents and cash, the patent stock is normalized by the firms' size. Figure 10 plots the distribution of each bin along with a fitted line. The upper left panel displays the correlation between liquidity

[24] 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.

[25] See Sun and Xiaolan (2019); Hall and Lerner (2010)

and innovation. A positive correlation between innovation and liquidity suggests that firms tend to rely on increased cash reserves as their innovativeness grows. However, substituting liquidity with leverage results in contrasting trends. The right panel illustrates that innovative firms are inclined to reduce their leverage. This finding reaffirms that financing R&D poses high costs, making it less likely for firms to resort to leverage as a means to fund their R&D. Consequently, borrowing is unlikely to explain the fluctuations in intangible investment subsequent to the shock. Therefore, the standard amplification mechanism where monetary policy affects asset collateral values and financial constraints is muted.

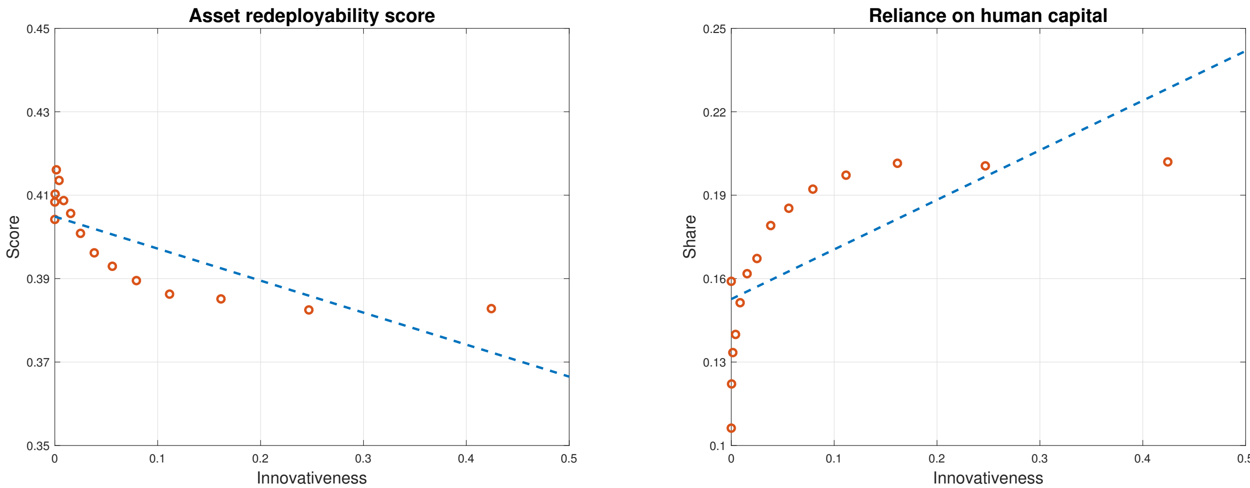
I now show that innovative firms holding cash is to pay adjustment costs, since intangible capital cannot be backed by outside financing. The role of liquidity in innovation is clear when companies can't obtain loans and are required to cover sizable adjustment expenses to drive innovation, especially when these costs are significant. High adjustment costs of intangible capital makes firm with high liquidity more likely to innovate than others. Following Döttling and Ratnovski (2021), I use a firm-level measure of asset redeployability and reliance on high-skilled human capital as a proxy for investment adjustment costs. A measure of asset redeployability is from Kim and Kung (2017). This measure reflects the investment adjustment costs as firms with redeployable assets can easily liquidate their capital. Hence, firms with high redeployable assets are likely to face low adjustment costs and vice versa. One issue with this measure is that this asset redeployability score may not reflect the adjustment costs of intangible capital. To supplement this issue, I also consider the high-skill labor share in a firm. Innovation is often carried out by a workforce that possesses advanced skills, as indicated by Sun and Xiaolan (2019). This implies that adjusting intangible investment is costly and takes time, as it is difficult to hire and fire talent. I compile industry-level data on the dependence on human capital by utilizing information obtained from the NBER-CES Manufacturing Industry Database.[26]

The figure presented in the left panel of Figure 11 illustrates a negative correlation between firm innovativeness and the redeployability of their assets. This suggests that, as firms increasingly rely on intangible capital, their assets tend to be more specific to the firm itself. Conversely, the right panel displays a positive correlation between firm innovativeness and their dependence on human capital. Both panels suggest that innovation is associated with significant adjustment costs.

However, this paper focuses on how firms' decisions change after monetary policy shocks. In this context, understanding how firms' marginal financing decisions shift after the shock becomes more pertinent. To test if adjustment cost plays important role in understanding heterogeneity in innovation responses arising from the level of liquidity, I run the regression

[26]The reliance on high-skilled human capital is defined as the income share of high-skill labor scaled by value added, with the income of high-skilled human capital is defined as total payroll net of production workers' wages following previous literature (See Pierce and Schott (2016); Döttling and Ratnovski (2021)).

Figure 11: Correlation between adjustment costs and innovations



Notes: This figure plots the correlation between firm's adjustment costs and innovation using the binned scatter plot with a fitted line. The last bin is dropped. The left panel shows the correlation between adjustment costs measured with the asset reployability from Kim and Kung (2017) and innovation. The asset redeployability score reflects usability of assets within and across industries. A high asset redeployability score implies low adjustment costs. The right panel shows the correlation between adjustment costs measured with the reliance on high-skilled human capital and innovation. High reliance on high-skilled human capital implies high adjustment costs. The innovativeness of firms is measured with patent stock divided by firms' total assets for normalization.

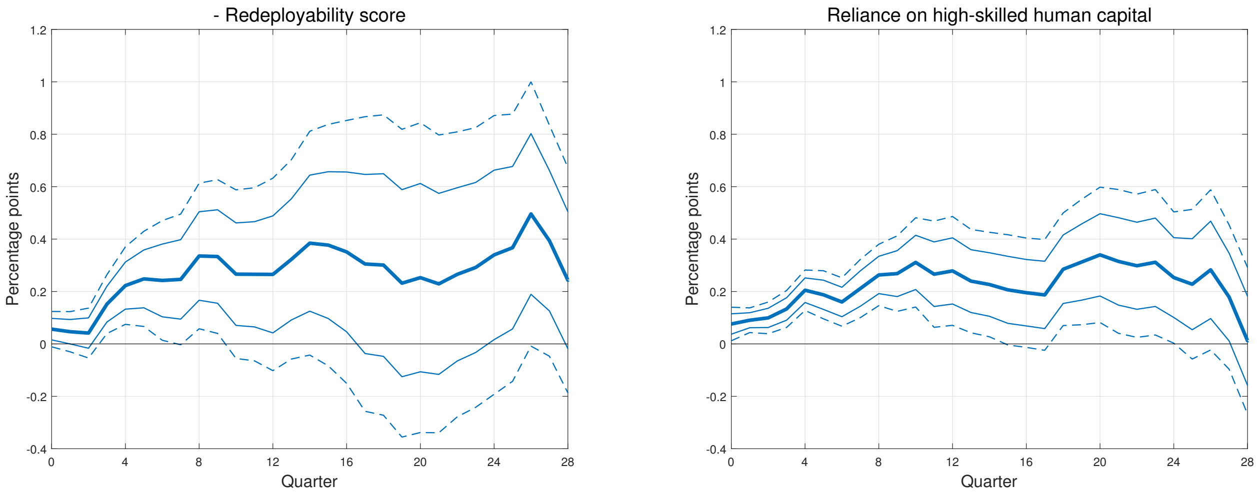
$$\begin{aligned}\Delta_h \log\left(\text{Innovation}_{j,t+h}\right) = \alpha_j + \alpha_{st} + \left(\Theta_h' + \varepsilon_t^m \Omega_h'\right) W_{jt-1} \\ + \beta_h \varepsilon_t^m L_{jt-1} A_j + \gamma_h \varepsilon_t^m A_j + \delta_h L_{jt-1} A_j \\ + u_{j,t+h},\end{aligned} \tag{5}$$

where L_{jt-1} denotes the liquidity of firms and A_j denotes the adjustment costs.[27] The idea is that that firms with low liquidity and minimal adjustment costs can innovate without much difficulty following an expansionary monetary policy shock, even when facing liquidity constraints. In contrast, companies with low liquidity and high adjustment costs are restricted by liquidity constraints since the expenses for adjustments must be covered internally, as highlighted in the above section. The primary parameter is represented by β_h. This parameter quantifies the influence of firms' adjustment costs on the impact of liquidity regarding an expansionary monetary policy shock.

Figure 12 displays my results. I modified the asset redeployability score by multiplying it by -1, with the intention of making it easier to understand that higher scores correspond to increased adjustment costs. The results, irrespective of the proxy used, underscore the significant role of liquidity when adjustment costs are large. For firms with adjustment costs one standard deviation higher, the impact of liquidity on the response to an expansionary monetary policy shock increases by 0.6 percentage points. Given that the coefficient of the interaction term between monetary policy

[27] L_{jt-1} is included in W_{jt-1}

Figure 12: Heterogeneous response of innovation to monetary policy shocks



Notes: This figure displays the dynamics of the interaction coefficient between liquidity, a proxy for adjustment costs, and monetary policy shocks, using specification 4. The innovation metric is computed from the number of patent filings. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

and liquidity is approximately 0.6, this figure holds substantial significance. I also conducted analysis using specification 4 on sub-groups, one with adjustment costs above the median and one with costs below. Figure A.19 shows the heterogeneous response of innovation stemming from liquidity following expansionary monetary policy shocks within each adjustment costs group, using the redeployability score as a measure. Similarly, Figure A.20 examines this response based on reliance on high-skilled human capital. The results show that after expansionary monetary policy shocks, high liquidity firms innovate more than low liquidity firms only when firms face high adjustment costs. These findings suggest that the heterogeneous response predominantly occurs within the high adjustment cost group, implying that cash reserves are likely being utilized to fund innovation, especially with regard to adjustment costs.

6 Conclusion

Innovation has profound effects on the macroeconomic environment. One of the major benefits of innovation is its contribution to economic growth. This 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 shocks to innovation is important for policymakers to make decisions about the interest rate 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. 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 shocks. 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. 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 real outcomes 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.

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A Additional results

A.1 Additional sources of heterogeneity

The key insight from the preceding analysis is the presence of divergence in innovation responses contingent upon firm characteristics. Additionally, firms characterized by high liquidity display the most pronounced reactivity to shocks, as they exhibit substantial growth in innovation subsequent to an expansionary monetary policy shock. This emphasizes the important role that liquidity plays in explaining such variability. In this section, I would provide other firm characteristics which contribute to the dispersion in innovation responses. Figure A.1 shows the result.

First, it's worth noting the significance of leverage. The question of whether firms are financially constrained is considered an essential factor in determining their investment choices (Ottonello and Winberry, 2020; Hori, 2020). In the primary analysis, I also incorporate leverage, as it commonly serves as a proxy for the extent of such constraints. Using the baseline measure, the estimated coefficient of the interaction term between the shock and leverage is both substantial and statistically significant. The result implies that after expansionary monetary policy shock, firms with high default risk are less responsive to monetary policy shocks. The result is similar to Ottonello and Winberry (2020) which investigates the response of tangible investment depending on the financial health after monetary policy shocks.

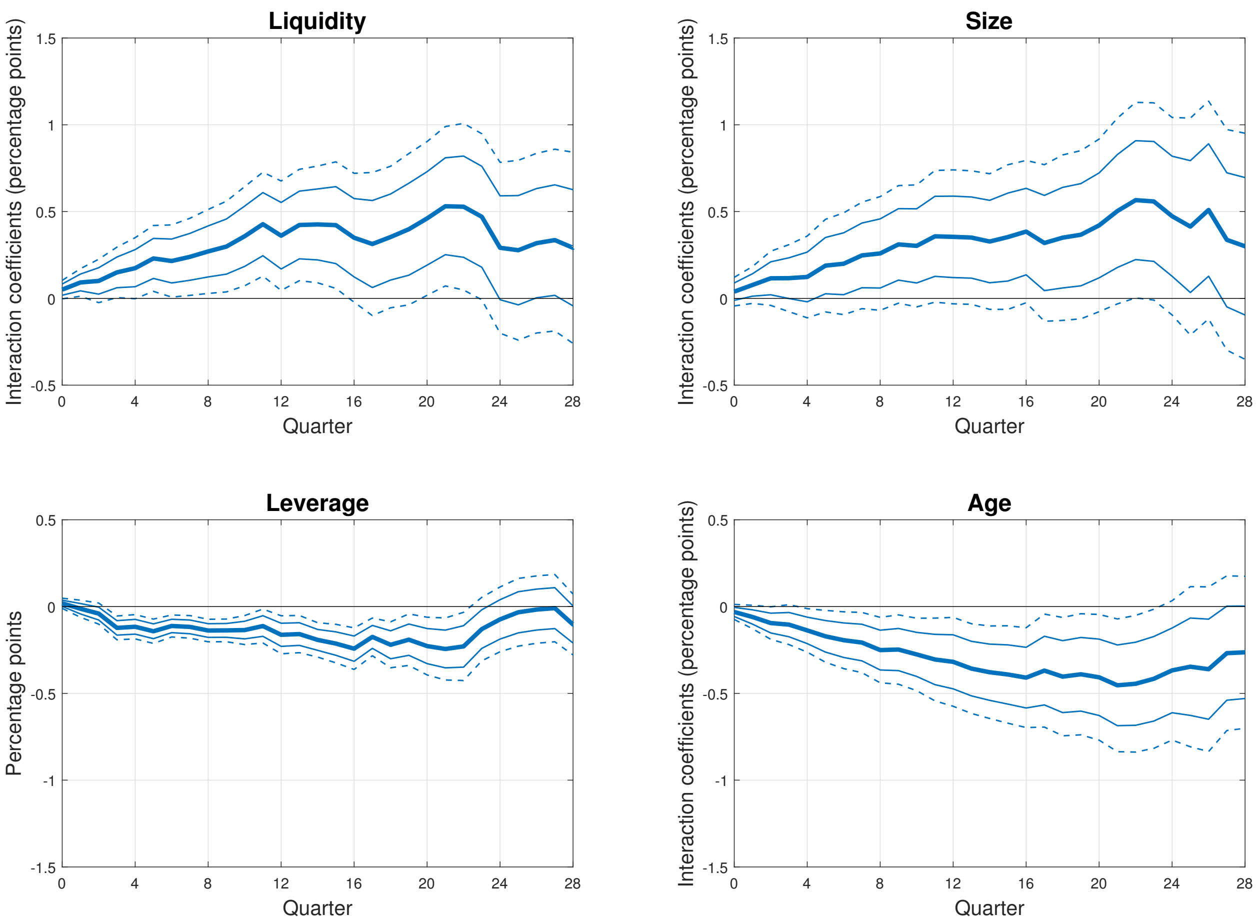
Next, age also seems important factor in determining the responses of innovation. The result shows that old firms are less innovative after the shock. This is also in line with the literature (Huergo and Jaumandreu, 2004). In addition, Durante, Ferrando, and Vermeulen (2022) points out that young firms are more sensitive to monetary policy shocks in terms of tangible investments. In this sense, the age of firms works in the same direction as young firms are more sensitive than old firms in terms of their innovation as well.

Moreover, the size of firms matter. The figure shows that larger firms are more responsive than small firms. This is opposite to previous literature (Gertler and Gilchrist, 1994) which show that small firms are tend to more sensitive to changes in the interest rate.

However, these outcomes were not robust when using alternative measure of innovation which lead to less precise coefficient estimates.

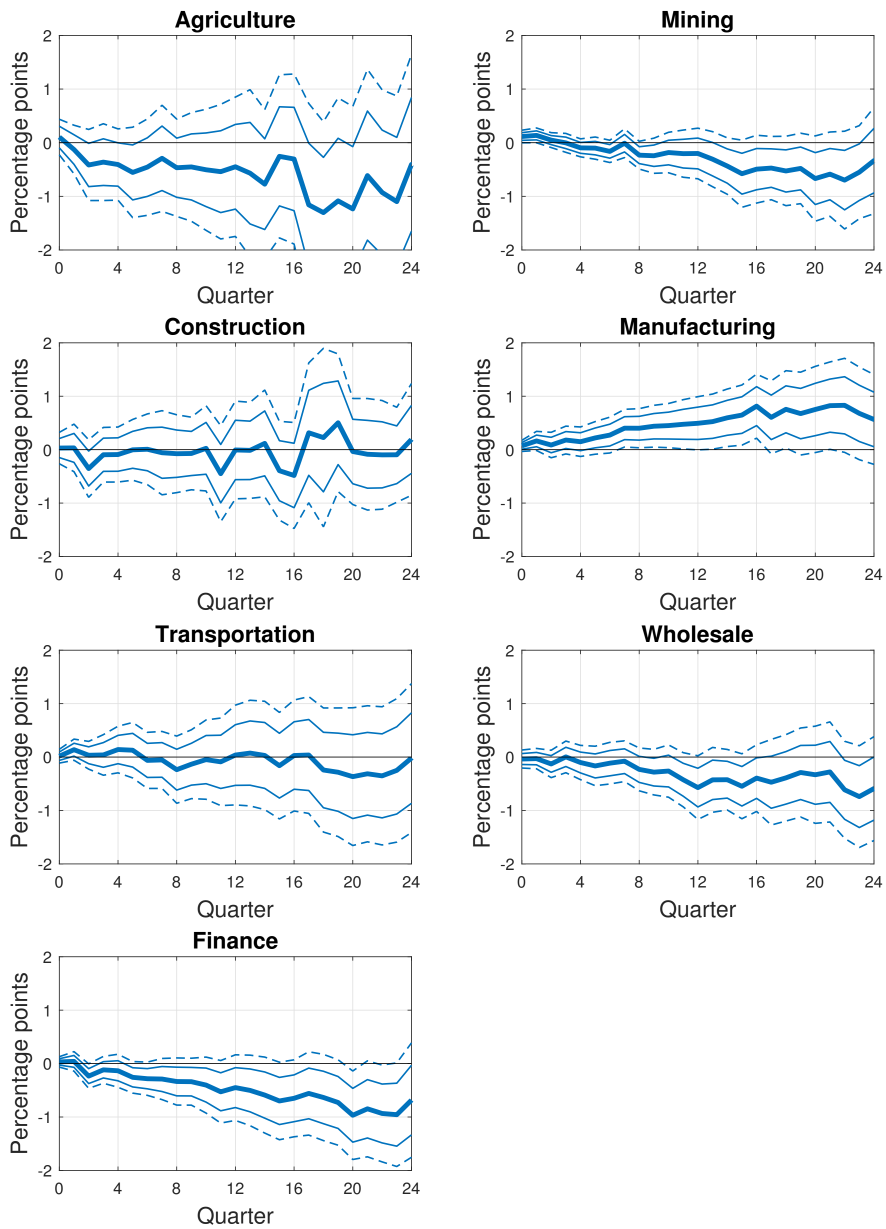
I also examine the relevance of industry-specific factors. As depicted in Figure A.2, it becomes evident that manufacturing firms exhibit more pronounced innovation responses following expansionary monetary policy shocks. Figure A.2 further illustrates that, on average, manufacturing firms possess a greater number of patents compared to firms in other sectors. When we combine these two observations, the findings suggest that the manufacturing sector plays a significant role in driving the aggregate innovation responses following such shocks.

Figure A.1: Heterogeneous response of innovation to monetary policy shocks



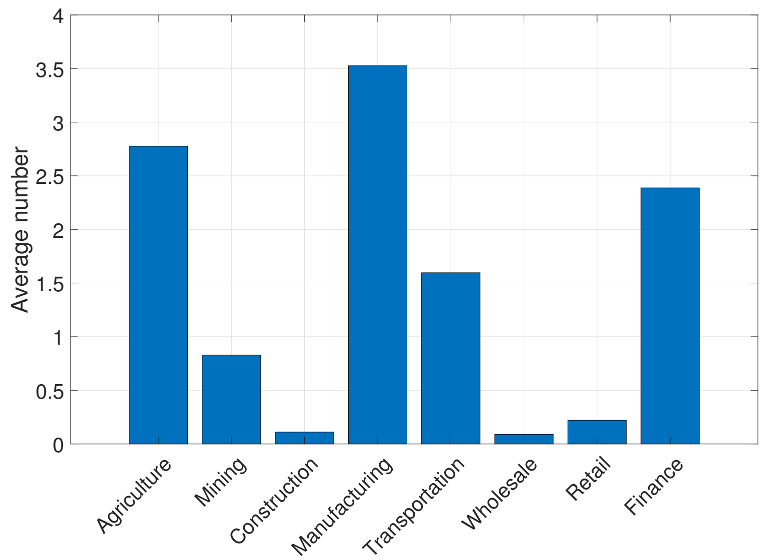
Notes: This figure displays the dynamics of the interaction coefficient between firm characteristics and monetary policy shocks. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively.

Figure A.2: Impulse response function of innovation to monetary shock by groups



Notes: This figure displays the impulse responses of the innovation metric to a negative, one standard deviation monetary policy shock for each industry group. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Those with liquidity above the median are defined as high-liquidity firms and the rest are defined as low-liquidity firms.

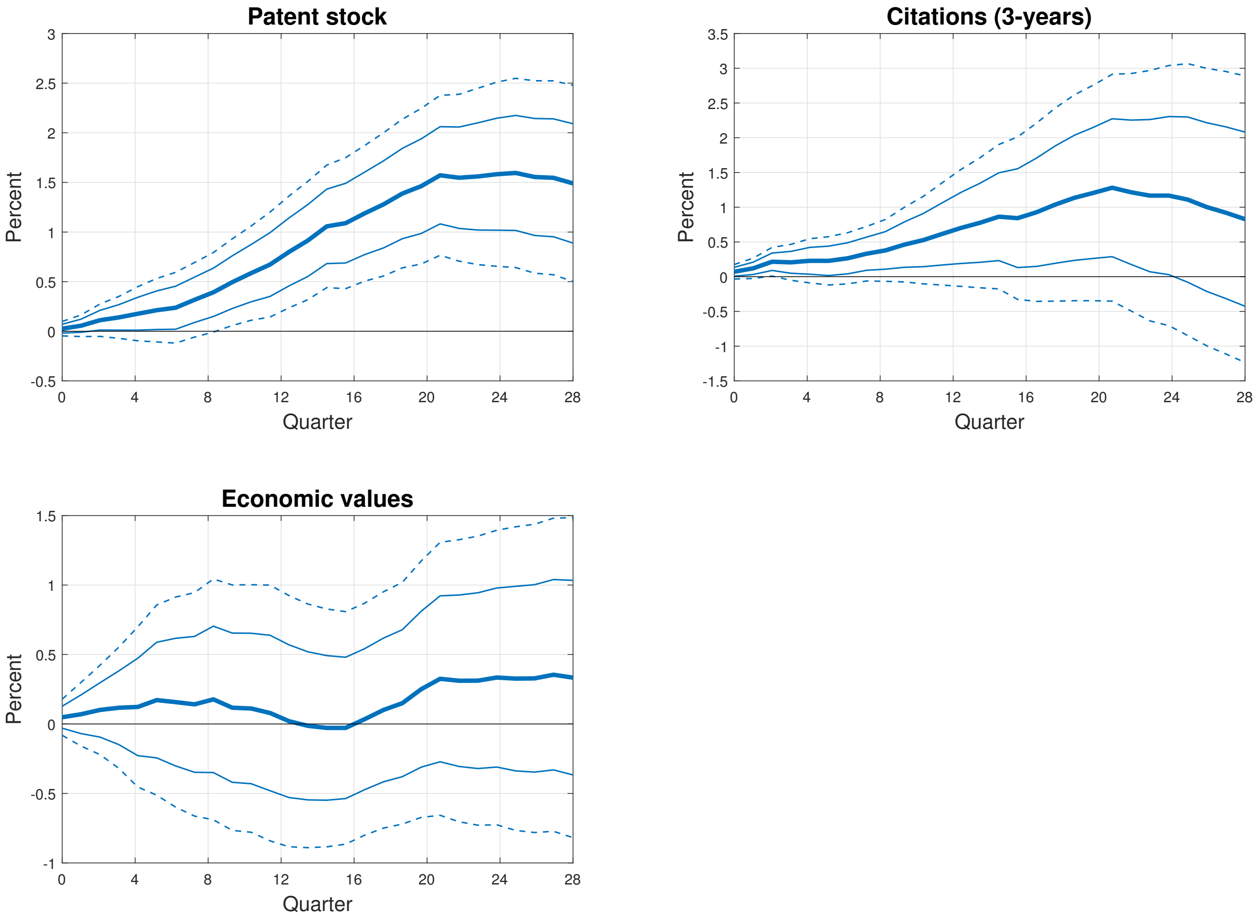
Figure A.3: Average number of patents by each industry



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

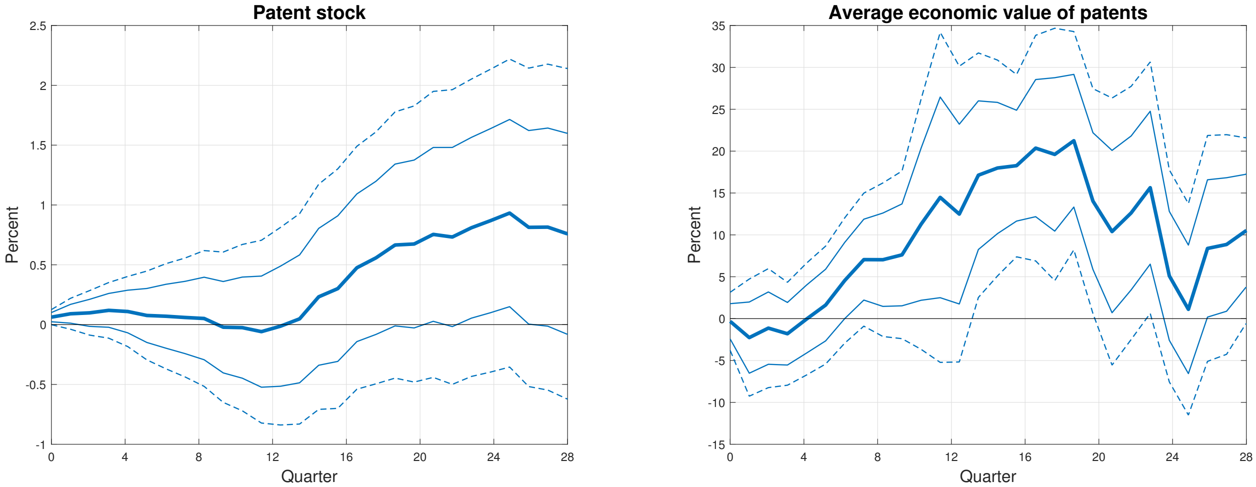
A.2 Robustness check

Figure A.4: Responses of innovation to monetary policy shock with various innovation metrics



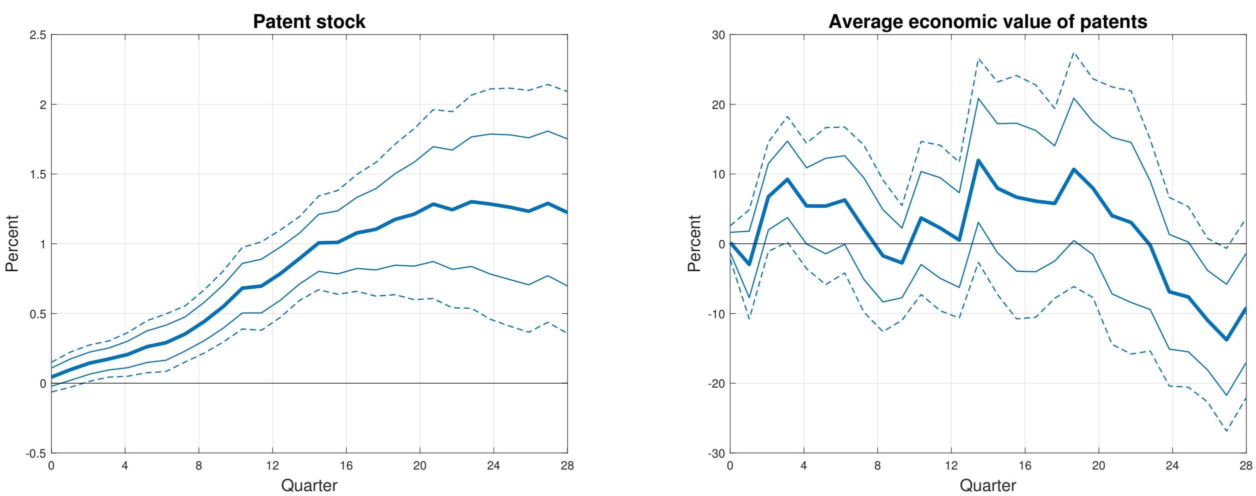
Notes: This figure displays the impulse responses of different aggregate innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.5: Responses of innovation to monetary policy shock with different monetary policy shocks



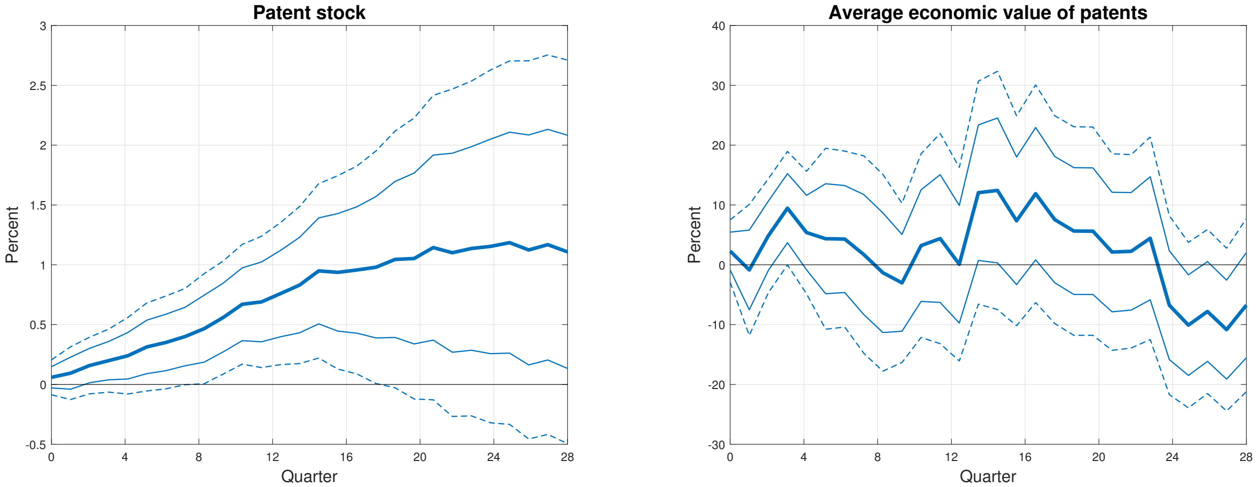
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Barakchian and Crowe (2013) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.6: Responses of innovation to monetary policy shock with different monetary policy shocks



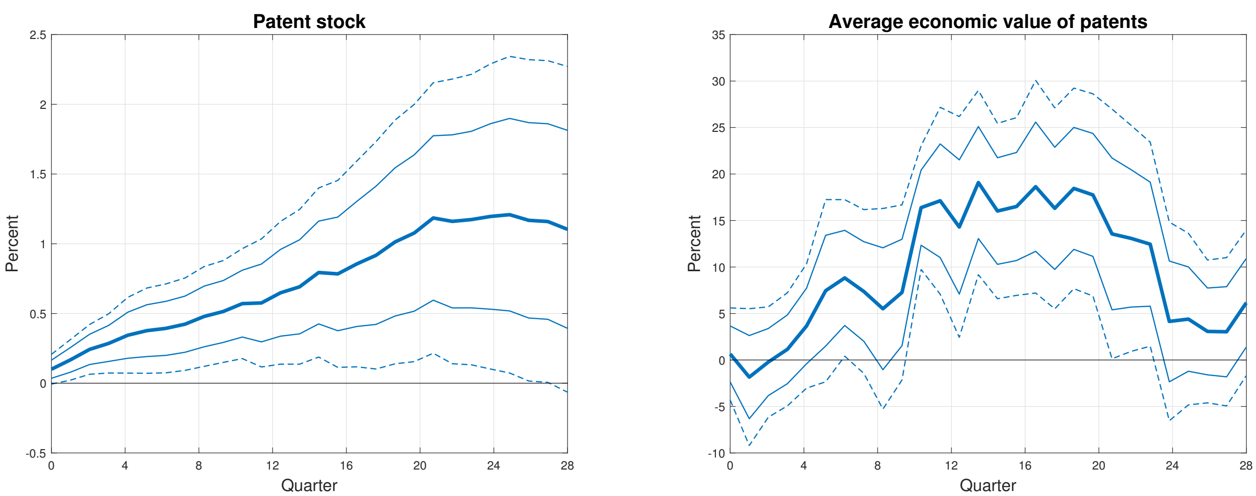
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Gertler and Karadi (2015) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.7: Responses of innovation to monetary policy shock with different monetary policy shocks



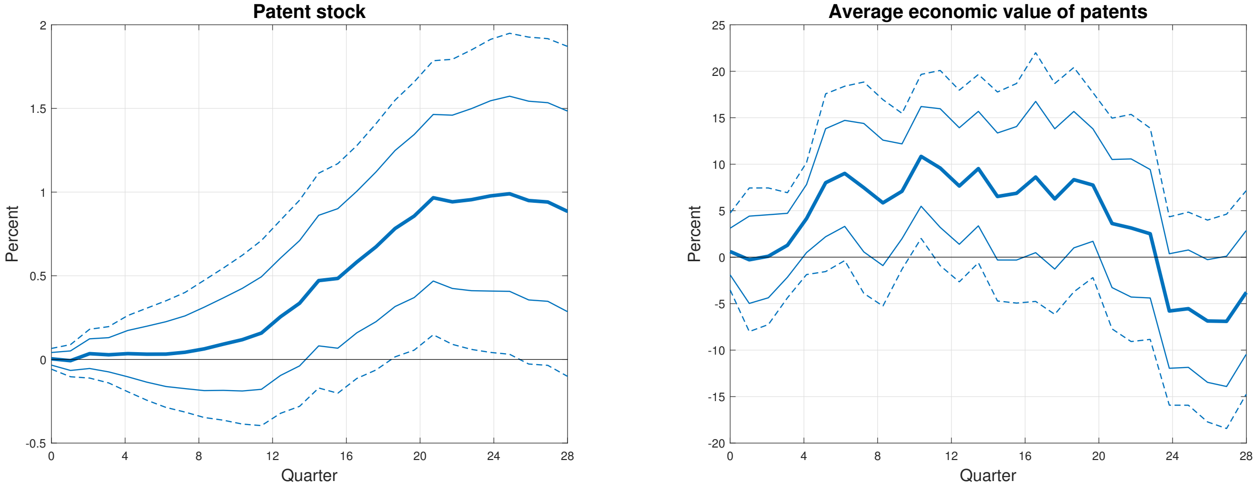
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Gorodnichenko and Weber (2016) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.8: Responses of innovation to monetary policy shock across varied time periods



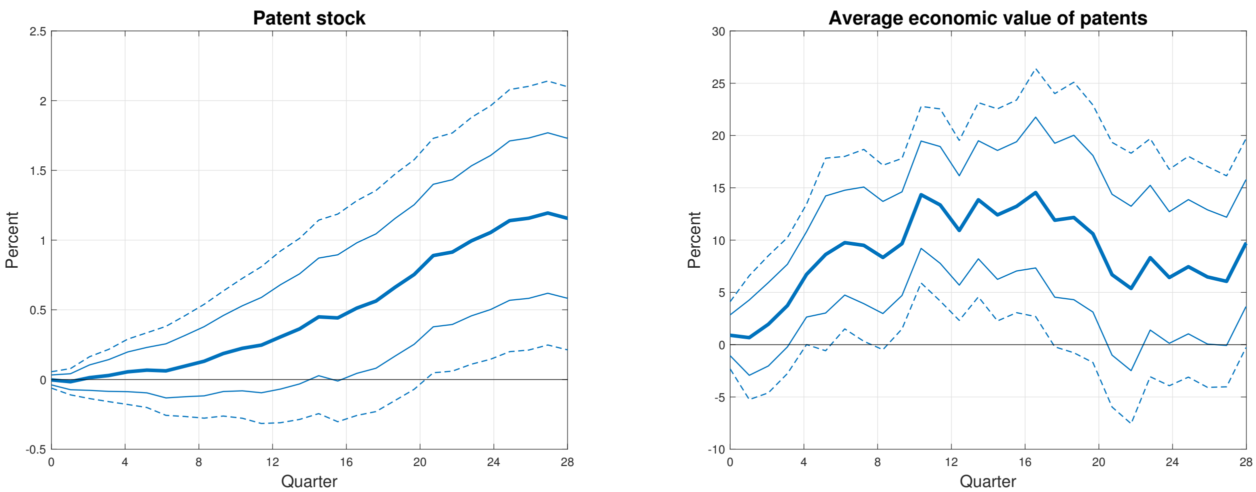
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Bauer and Swanson (2022) and the sample period starts from 1995Q2 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.9: Responses of innovation to monetary policy shock across varied time periods



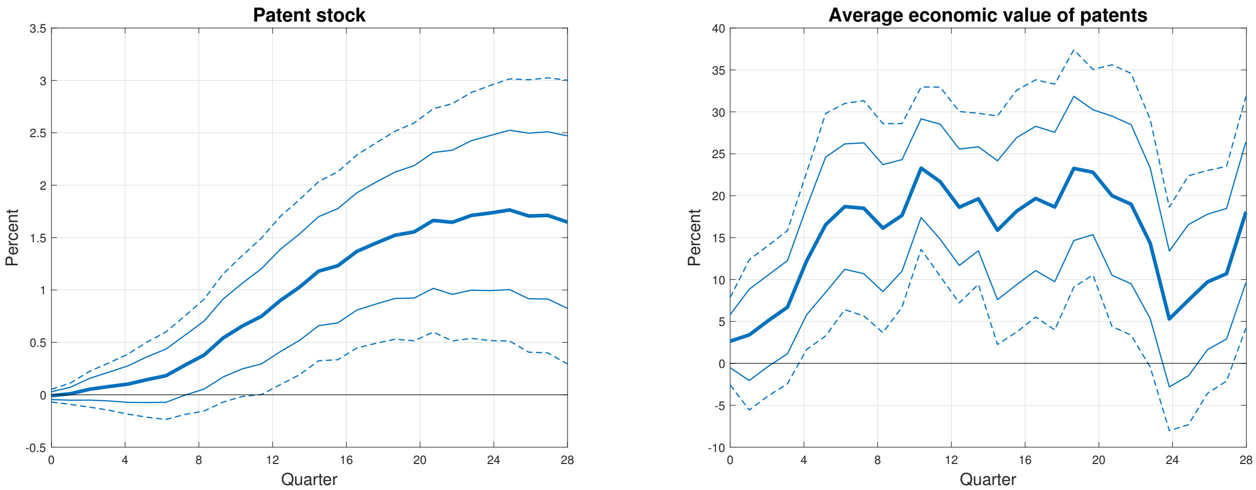
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends up to 2011Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.10: Responses of innovation to monetary policy shock with varied controls



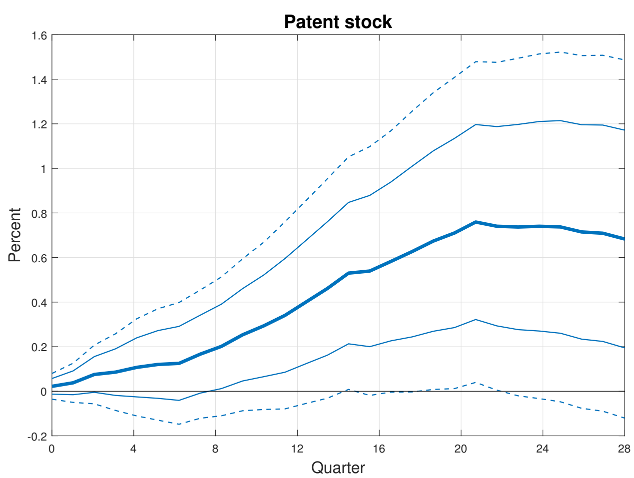
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3 with J = 4 and I = 4. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.11: Responses of innovation to monetary policy shock with varied controls



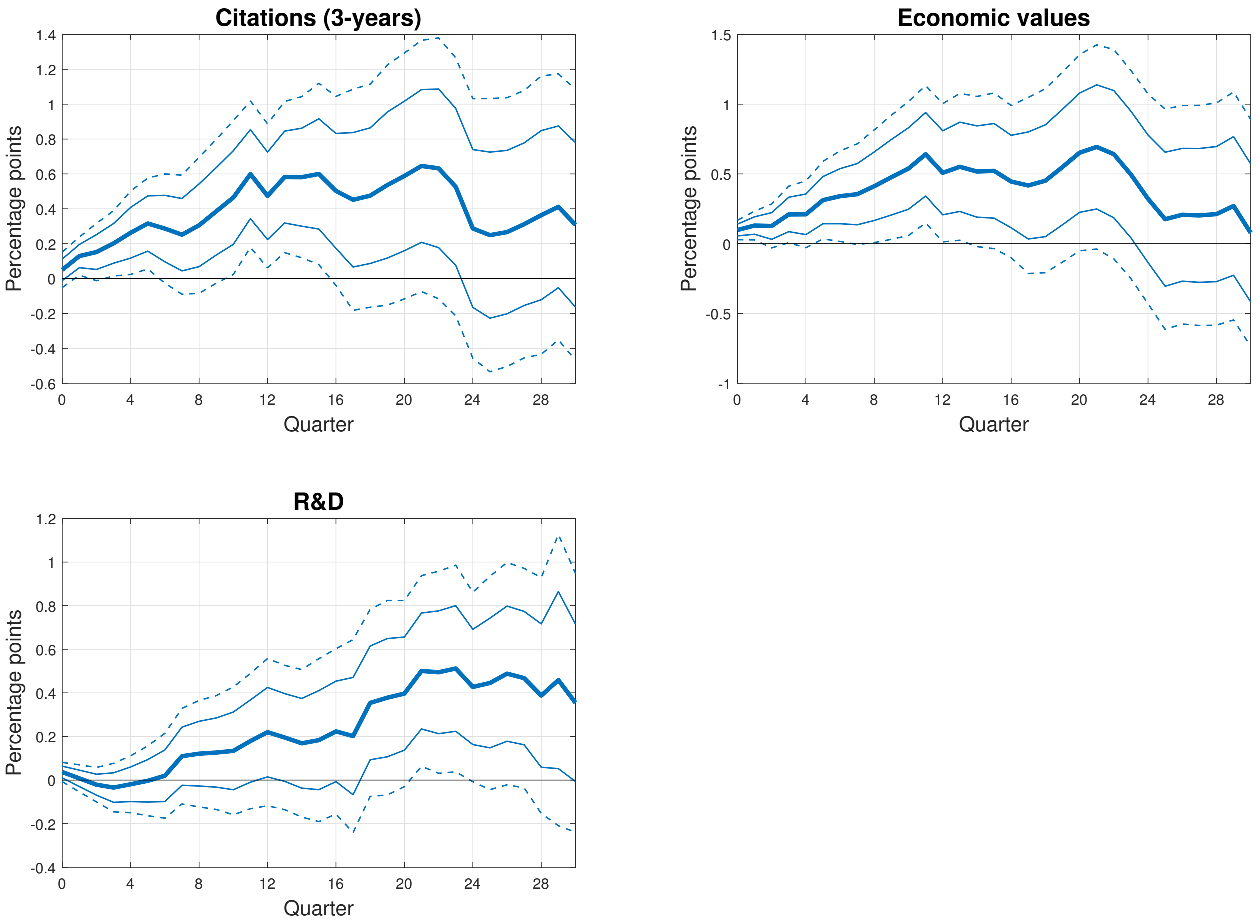
Notes: This figure displays the impulse responses of the innovation metrics to a negative, one standard deviation monetary policy shock using specification 3 with J = 8 and I = 8. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.12: Responses of innovation to monetary policy shock with continuous depreciation



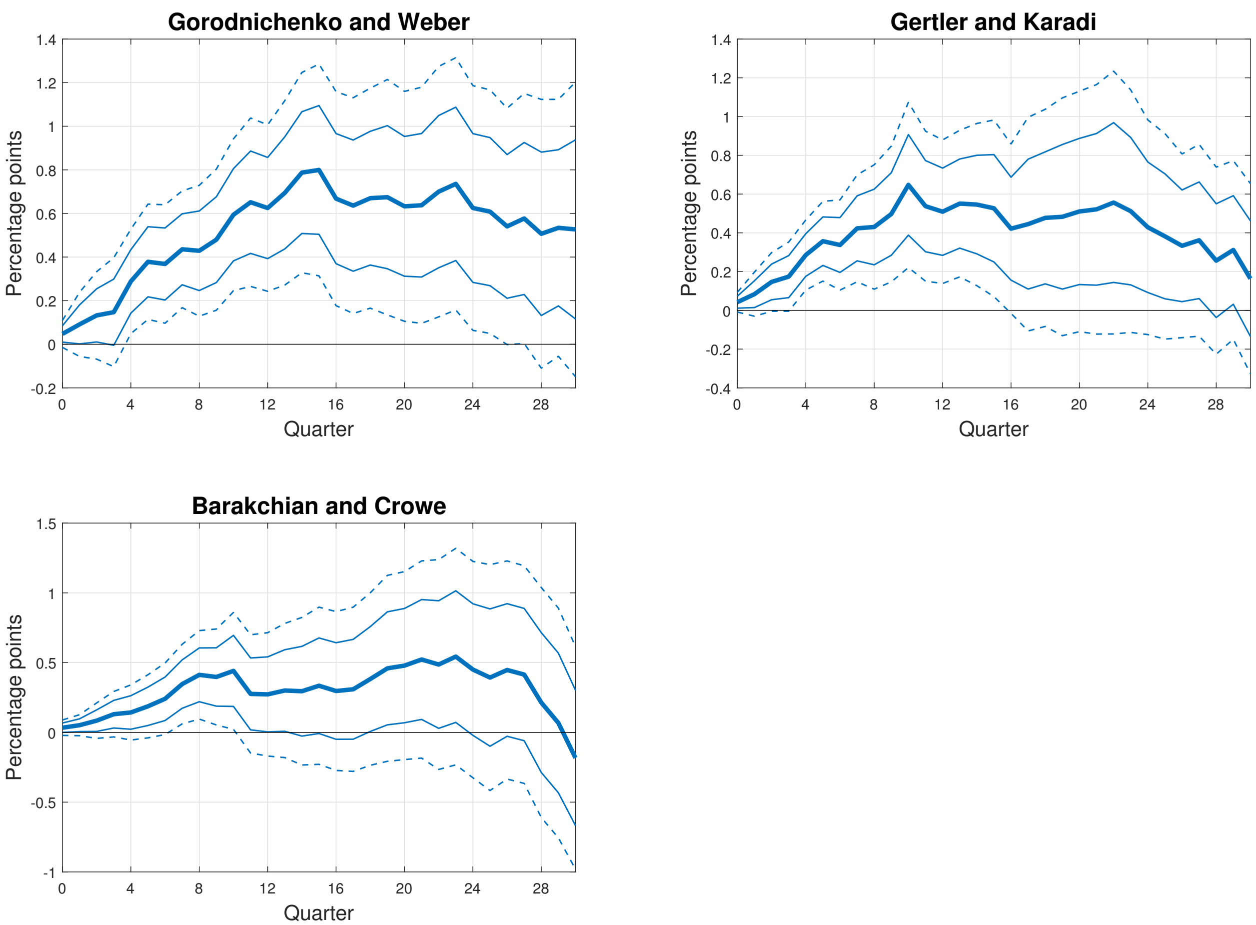
Notes: This figure displays the impulse responses of the innovation metrics, using patent stock constructed with continuous depreciation of patents, to a negative, one standard deviation monetary policy shock using specification 3. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.13: Heterogeneous response of innovation to monetary policy shocks with various innovation metrics



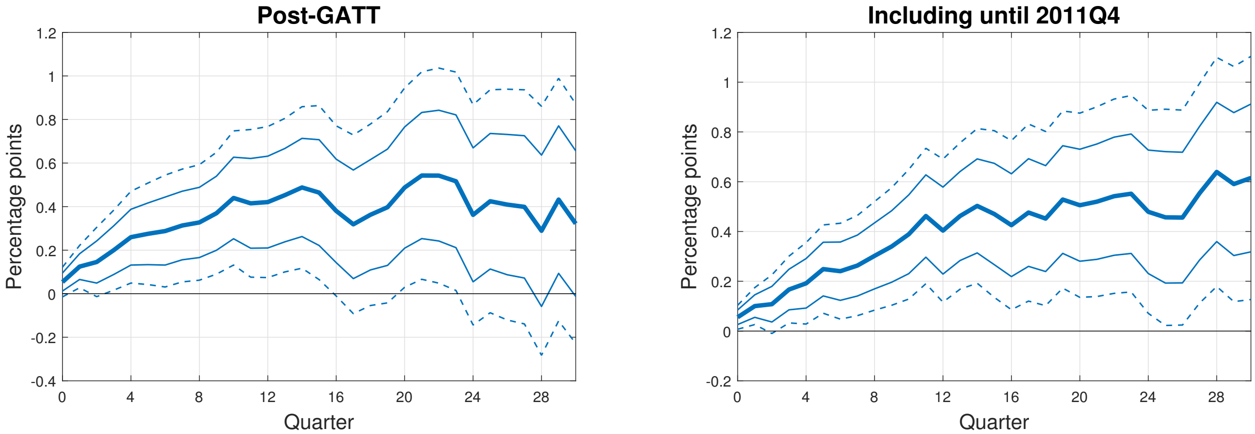
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks across various innovation metrics, using the specification 4. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure A.14: Heterogeneous response of innovation to monetary policy shocks with different monetary policy shocks



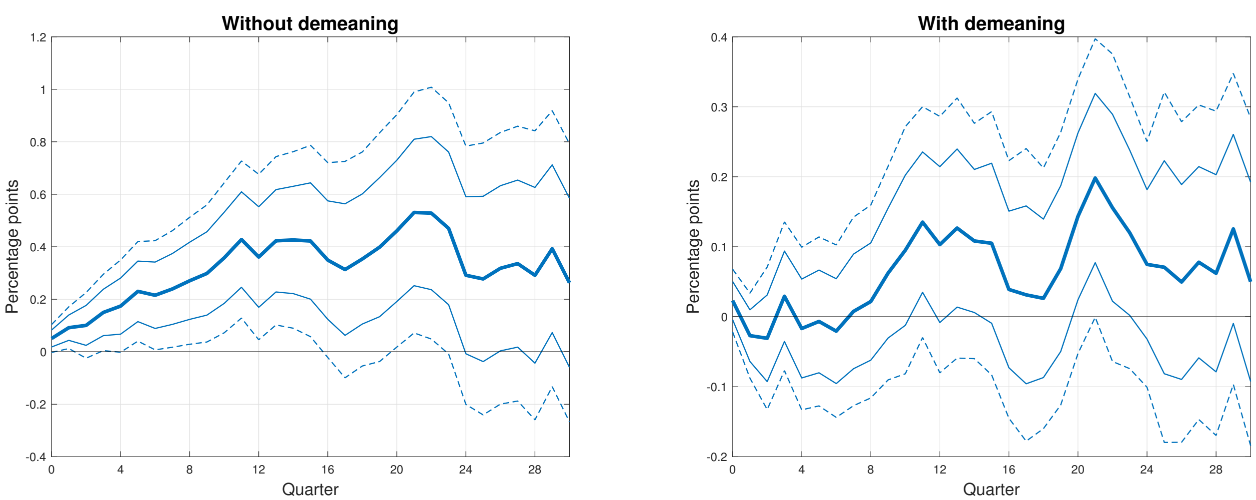
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4. The monetary policy shock is from Gorodnichenko and Weber (2016), Gertler and Karadi (2015), and Barakchian and Crowe (2013). The sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure A.15: Heterogeneous response of innovation to monetary policy shocks across varied time periods



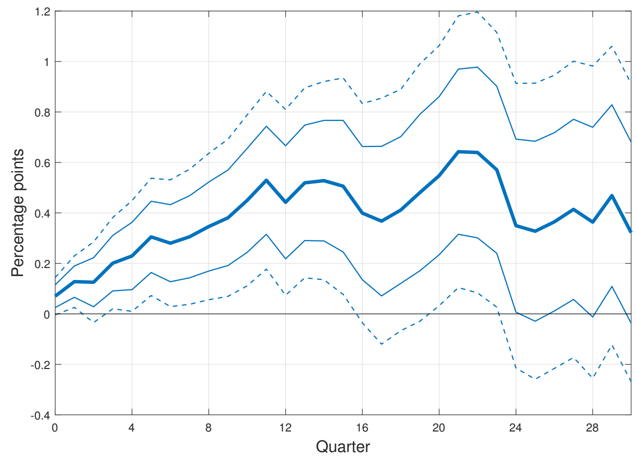
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4. The monetary policy shock is from Bauer and Swanson (2022). In the left panel, the sample period covers the period from 1995Q2 to 2011Q4, with the analysis of monetary policy shocks ending at 2007Q4. In the right panel, the sample period extends from 1988Q1 to 2011Q4, and the analysis of monetary policy shocks covers the entire period up to 2011Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure A.16: Heterogeneous response of innovation to monetary policy shocks with demeaning variables



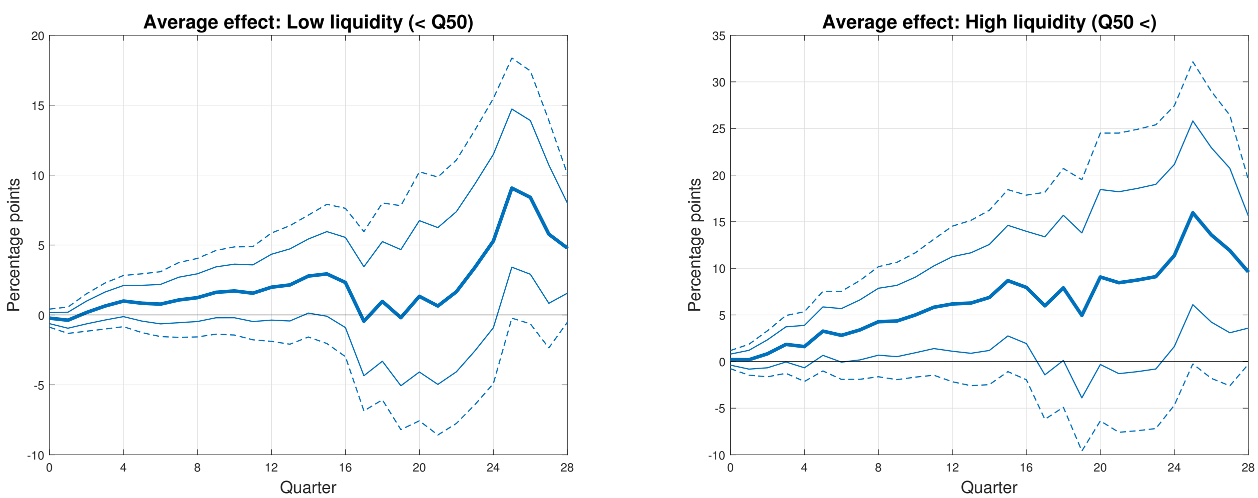
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, with demeaned variables, using the specification 4. The monetary policy shock is from Bauer and Swanson (2022). The sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure A.17: Heterogeneous response of innovation to monetary policy shocks among firms with at least one patent filing



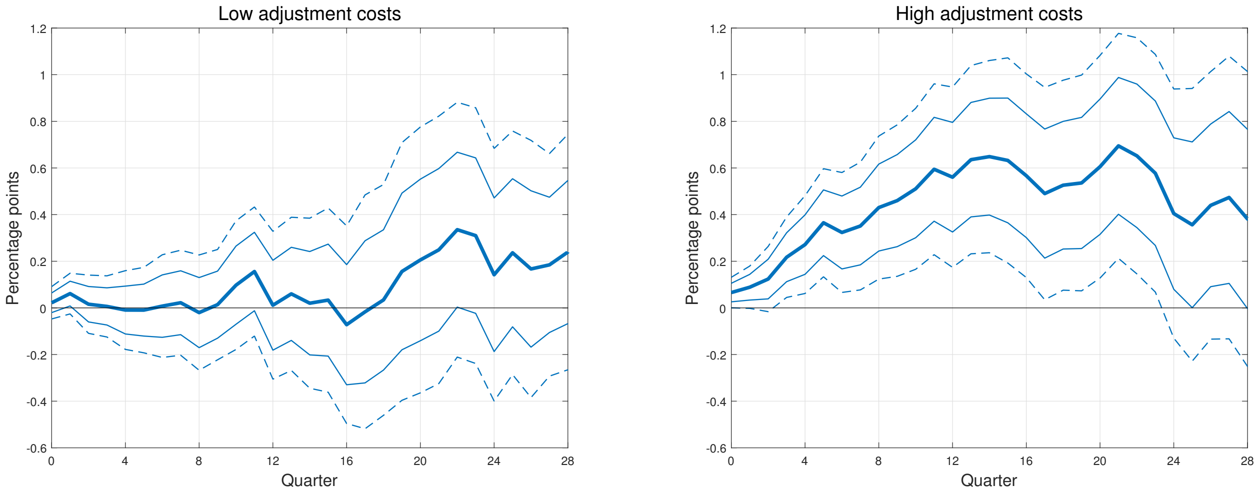
Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after, and it includes only firms with at least one patent filing. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

Figure A.18: Impulse response function of innovation to monetary shock by groups



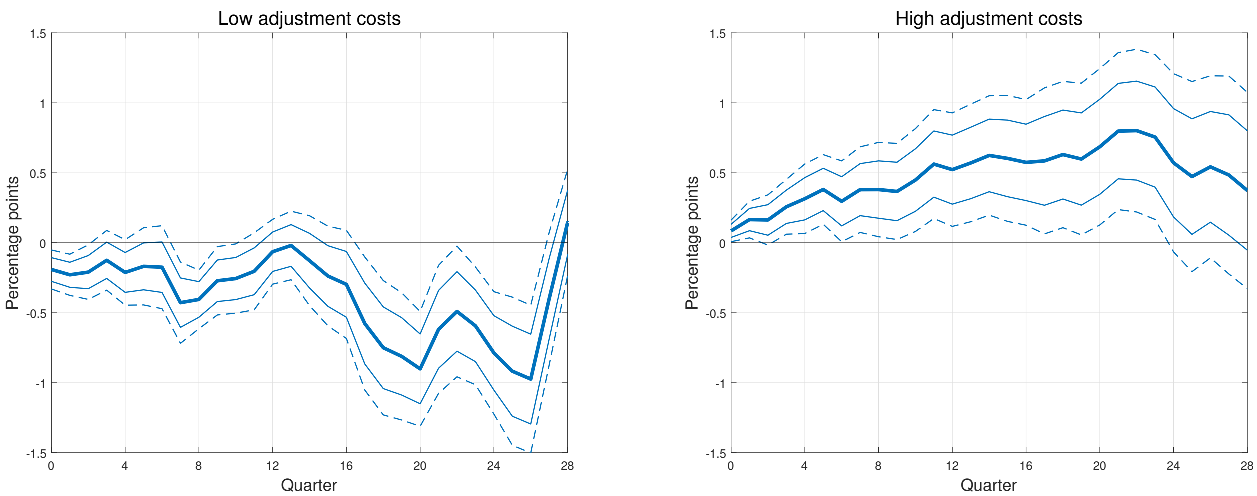
Notes: This figure displays the impulse responses of the innovation metric to a negative, one standard deviation monetary policy shock for each liquidity group. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. 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.

Figure A.19: Heterogeneous response of innovation to monetary policy shocks



Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4 for each adjustment costs group. The innovation metric is measured using the number of patent filings, while the adjustment cost is proxied by the asset redeployability score. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

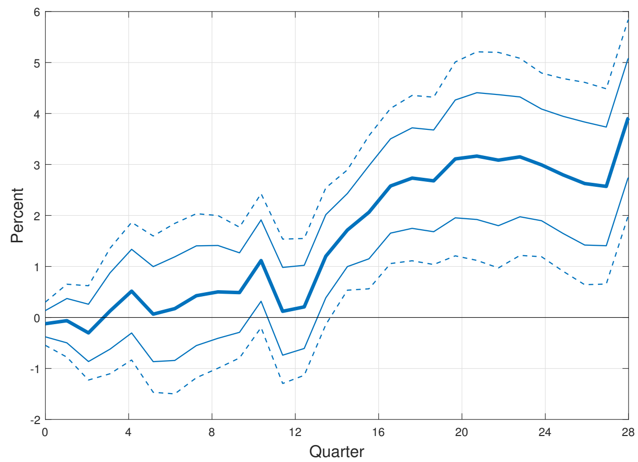
Figure A.20: Heterogeneous response of innovation to monetary policy shocks



Notes: This figure displays the dynamics of the interaction coefficient between liquidity and monetary policy shocks, using the specification 4 for each adjustment costs group. The innovation metric is measured using the number of patent filings, while the adjustment cost is proxied by reliance on high-skilled human capital. The monetary policy shock is from Bauer and Swanson (2022) and the sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are two-way clustered by firms and quarter.

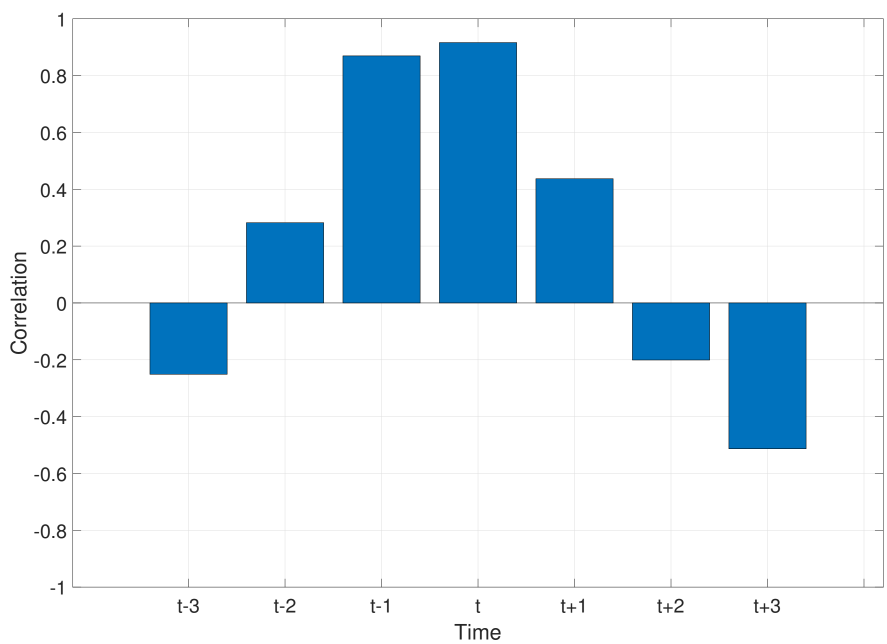
A.3 Other results

Figure A.21: Effect of patent application on TFP



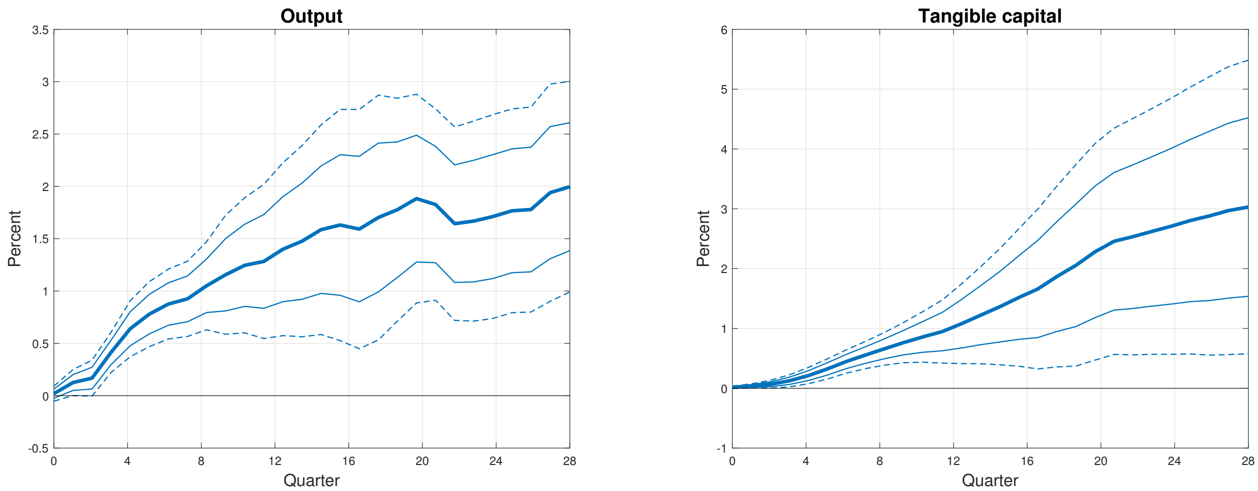
Notes: This figure plots the impulse response of TFP to changes in patent application. Specification 3 is used where x denotes TFP and z denotes patent application. A lag order of J = 4 and an order of I = 4 are used. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.22: Correlation between innovation and intangible capital



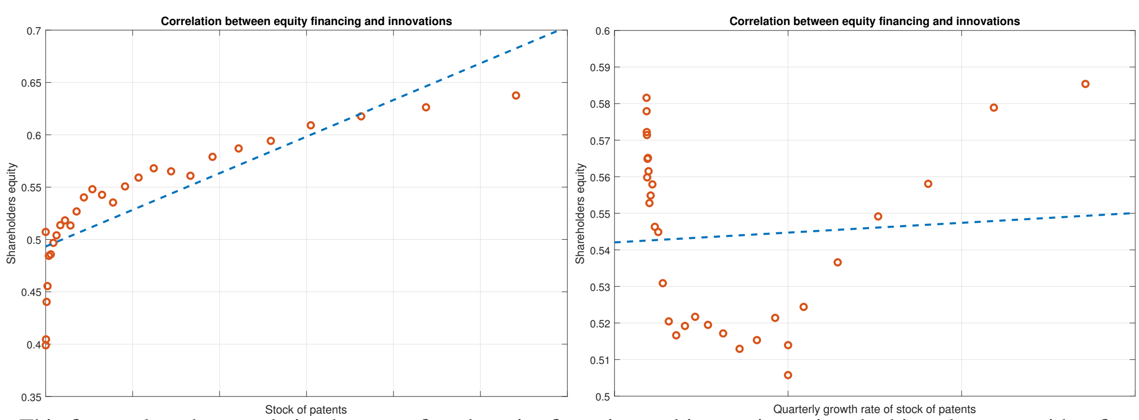
Notes: This figure plots the correlation between cyclical components of Patent stock$_t$ and Intangible capital stock$_{t+j}$ where j = -3, ..., 3

Figure A.23: Response of macro variables to monetary policy shocks



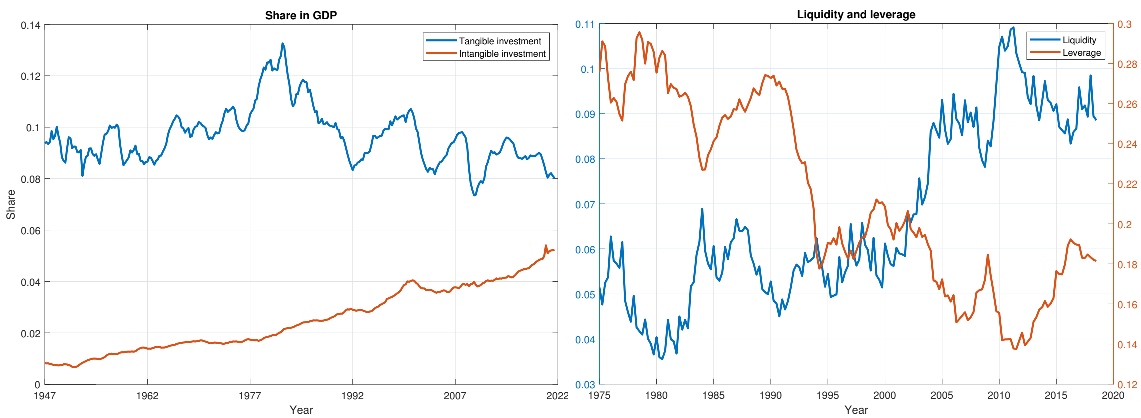
Notes: This figure displays the impulse responses of aggregates to a negative, one standard deviation monetary policy shock using specification 3. Quarterly TFP is from Fernald (2014), and monetary policy shock is from Bauer and Swanson (2022). The sample period spans from 1988Q1 to 2011Q4, while the analysis of monetary policy shocks extends only up to 2007Q4. The sample is restricted to avoid estimating the effect between the period before GATT and the period after. The dashed and continuous lines represent confidence intervals at one and 1.65 standard deviations, respectively. Standard errors are as in Driscoll and Kraay (1998) to allow for arbitrary serial and cross-sectional across horizons and time.

Figure A.24: 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.25: 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

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	$\frac{\text{cash and short-term investment}}{\text{total assets}}$	$\frac{\text{CHEQ}_{i,t}}{\text{ATQ}_{i,t}}$	Compustat
Leverage	$\frac{\text{total debt}}{\text{total assets}}$	$\frac{\text{DLCQ}_{i,t}+\text{DLTTQ}_{i,t}}{\text{ATQ}_{i,t}}$	Compustat
Age	based on the incorporation date		WorldScope
Size	book value of assets	$\log(\text{ATQ}_{i,t})$	Compustat
EBITDA		$100 * \frac{\text{SALEQ}_{i,t}-\text{COGSQ}_{i,t}-\text{XSGAQ}_{i,t}}{\text{IPD}_{i,t}}$	Compustat
Tobin's Q		$\frac{\text{ATQ}_{i,t}+\text{PRCCQ}_{i,t}*\text{CSHOQ}_{i,t}-\text{CEQ}_{i,t}+\text{TXDITCQ}_{i,t}}{\text{ATQ}_{i,t}}$	Compustat
Real sales growth		$100 * \Delta\log(100 * \frac{\text{SALEQ}_{i,t}}{\text{IPD}_{i,t}})$	Compustat
Net receivables to sales		$\frac{\text{RECTQ}_{i,t}-\text{APQ}_{i,t}}{\text{SALEQ}_{i,t}}$	Compustat
Current assets over total assets		$\frac{\text{ACTQ}_{i,t}}{\text{ATQ}_{i,t}}$	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.