Essays on Firms, Finance, and Macroeconomy

by

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DEDICATION

To myself–for persevering; and to my husband–for making it possible.

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ABSTRACT

This dissertation consists of three chapters examining how financial constraints and financial innovation influence firm-level decisions on investment, labor allocation, and financing choices. The first two chapters, joint work with Tereza Ranošová, combine firm-level empirical analysis with a structural macroeconomic model to investigate how firm leverage shapes the transmission of monetary policy, particularly through substitution between capital and labor inputs. The third chapter uses detailed transaction-level data on security issuances to classify financial innovation in U.S. capital markets and assess its impact on firm growth. Across these chapters, I emphasize how differences in financial flexibility and access to innovative financial instruments drive substantial heterogeneity in firm-level outcomes, influencing both firm responses to monetary policy and long-run growth trajectories.

Chapter 1, "Financial Frictions and the Labor-Capital Tradeoff in Monetary Policy Transmission" (joint with Tereza Ranošová), takes an empirical look at how firm leverage influences the effects of monetary policy. Using firm-level data from Compustat and monetary shocks identified through high-frequency futures markets, we estimate how firms with different levels of debt respond to interest rate changes. The findings are striking: more leveraged firms tend to hire more workers in response to monetary easing but invest less in capital. Sales, however, don't differ much across firms. This suggests that constrained firms aren't necessarily growing faster—they're changing how they produce, shifting away from capital toward labor. These results challenge the typical view that firms expand inputs proportionally when financing becomes cheaper, pointing to the need for models that allow input substitution.

Chapter 2, "A New Keynesian Model of Capital-Labor Substitution under Financial Constraints" (joint with Tereza Ranošová), develops a heterogeneous-firm New Keynesian model to interpret empirical evidence on how financial constraints affect firms' labor and capital decisions in response to monetary policy. The model incorporates two types of wholesale firms that differ by leverage, face occasionally binding collateral and dividend constraints, and use flexible constant elasticity of substitution (CES) production technologies. In contrast to the standard Cobb-Douglas setup, the CES production structure allows capital and labor inputs to respond asymmetrically to policy shocks. We calibrate the model to match

empirical patterns documented in Chapter 1, specifically the observed phenomenon that more leveraged firms increase employment but decrease investment in response to monetary easing. At the aggregate level, the model predicts that higher firm leverage dampens investment responses, thereby initially muting employment reactions, but subsequently amplifies employment through capital-labor substitution. These findings demonstrate how firm-level financial frictions and production flexibility jointly shape the macroeconomic transmission of monetary policy.

Chapter 3, "Financial Innovation and Firm Growth: Evidence from New Securities in U.S. Capital Markets", examines the role of financial innovation in firm growth. Using detailed data from SDC Platinum, I create a new classification of over 8,500 distinct debt and equity instruments issued by U.S. non-financial firms between 1970 and 2020. These instruments vary along dimensions such as maturity, convertibility, payment structure, and legal design—features that have not previously been systematically studied. Linking these data to firm-level balance sheets, I show that large, mature firms predominantly introduce new securities. However, among innovators, early adopters tend to grow faster in sales, investment, and employment. These findings indicate financial innovation isn't merely a result of firm growth; it can actively enable expansion.

CHAPTER 1

Financial Frictions and the Labor-Capital Tradeoff in Monetary Policy Transmission[1]

1.1 Introduction

Since the Great Recession, the Federal Reserve has embarked on a path to normalize monetary policy, raising interest rates towards pre-crisis levels, adjusting the pace according to the economy's performance. These efforts are designed to bolster the Fed's ability to achieve its goals under ''dual mandate", with equal emphasis on both full employment and price stability. [2]

At the same time, the importance of a force that may alter the efficacy of the transmission of the monetary policy–financial frictions–have also grown. A common proxy to those, aggregate leverage—defined as the ratio of nonfincial corporate debt to GDP—has been on a steady upward trajectory, reaching historically high 78%[3]. The quality of this debt has worsened, with BBB-rated bonds, the riskiest slice of investment-grade securities, now making up half of that market. While the literature has mostly focused on the role of financing constraints in transmission to investment, it is less clear what this means for the ability of the Fed to meet its objectives on employment.

This paper addresses this question by examining whether financial frictions dampen or amplify the transmission of monetary policy to firms' employment, in the cross-section as well as on the aggregate, and why. We begin by providing evidence of heterogeneity in firm-level responses to monetary policy, using annual monetary shocks combined with firms' balance sheet information from Compustat. Additionally, we analyze other firm-level variables to

[1] joint with Tereza Ranošová

[2] Chair Jerome H. Powell, "New Economic Challenges and the Fed's Monetary Policy Review," August 2020.

[3] According to IMF Global Debt database in 2022.

explore potential mechanisms behind the role of leverage in shaping labor demand responses.

We find that monetary policy has a stronger impact on labor demand when of firms that are more leveraged, while the effect on capital investment moves in the opposite direction. Interestingly, we observe no significant heterogeneity in sales responses across firms. While consistent findings on labor demand and capital investment separately have been documented in previous studies (see Bahaj et al. (2022) for employment and Ottonello and Winberry (2020) for investment), our analysis uniquely combines these dimensions within a unified setting. Our insight is that firms with higher-than-average leverage shift to a significantly less capital-intensive mode of production following an expansionary monetary shock without affecting their overall output by much. Previous work often focuses on a single aspect—such as investment or employment—when evaluating how financial frictions influence monetary policy transmission. Our study shows that this narrow focus can lead to misleading conclusions about the overall firms' responsiveness, as firms' capital and labor responses may diverge.

In our empirical analysis, we use a panel local projection method to estimate both the immediate and dynamic impacts of monetary shocks, identified through the high-frequency event-study approach. We construct a series of annualized monetary surprises from 1990 to 2007 and merge it with firm-level balance sheet data from Compustat. The dataset includes information on employment, investment, sales, and other characteristics for 5,243 non-financial firms, varying in size from 19 to 115 thousand employees. To assess the variation in response across firms, we interact the monetary policy shock with firm leverage. Following the methodology of Ottonello and Winberry (2020), we concentrate on within-firm changes in leverage, ensuring that long-term differences between firms do not affect our key findings regarding firms' sensitivity to monetary policy. Firm fixed effects are included to control for permanent firm-specific traits, and sector-by-quarter fixed effects are added to account for sectoral responses to aggregate shocks. While we treat the monetary policy shock as exogenous, additional controls are included beyond leverage to capture firm heterogeneity that could be linked to leverage or firms' varying sensitivities to monetary policy. These controls also help account for potential cyclical differences across firms that are unrelated to the monetary policy shocks themselves.

We find that within the first year following a one standard deviation cut in interest rates, a firm with leverage 1 standard deviation higher (around 37 percentage points) increases employment by 0.55 percentage points more than the average firm. The point estimates remain elevated over the five year horizon, indicating a persistent effect. The effect of

leverage on firms' investment responsiveness to monetary policy is similar in magnitude but opposite in sign. The differential response of sales to a monetary policy shock is zero on average over a 5-year horizon and statistically insignificant in every period (with a temporary shift from positive to negative midway through the period).

Our research builds upon several strands of literature that examine the impact of financial frictions and firm heterogeneity on monetary policy transmission. While earlier studies have explored either the investment or employment responses to monetary policy in isolation, we contribute by examining both dimensions within a single framework. By doing so, we highlight the interaction between capital and labor decisions and the role of leverage in shaping firms' responses to monetary policy shocks.

This paper is the first to document that more leveraged firms exhibit a stronger labor demand response to monetary policy in the U.S., using firm-level microdata. Our study adds to the findings of Bahaj et al. (2022), who demonstrate that more leveraged and younger firms in the UK exhibit stronger labor demand responses to monetary policy.[4][5] Unlike Bahaj et al. (2022), our study considers within-firm changes in leverage over time, isolating the impact of leverage from permanent differences in firms' responses, providing a clearer view of how leverage alone amplifies firms' sensitivity to monetary shocks.

In the U.S. context, our research differs from existing studies on employment responses to monetary policy, such as Singh et al. (2023) and Yu (2022). Both Singh et al. (2023) and Yu (2022) document that smaller and younger firms exhibit stronger labor demand reactions to monetary policy. However, our specification offers several advantages. First, we employ a panel local projection method combined with firm-level balance sheet data, capturing both immediate and dynamic impacts of monetary shocks. This contrasts with the approach used by Singh et al. (2023), who utilize state-sector level data from the Quarterly Workforce Indicators dataset, with data grouped by firm characteristics. While detailed firm characteristics such as size and industry are reported, the dataset lacks other balance sheet information. Similarly, Yu (2022) uses firm-level microdata but includes only basic characteristics such as age and size, without key variables like leverage or total assets, making it difficult to account for confounding factors that may influence firms' responses to monetary policy.

Evidence from other countries on employment responses to monetary policy reveals similar

[4]They use a broad definition of leverage as the ratio of total liabilities to total assets, where liabilities may include accounts payable, pension obligations, income tax liabilities, contingent liabilities, and sales taxes.

[5]Age of the firm is measured as the number of years since incorporation.

patterns of heterogeneity. Jasova et al. (2023) find that smaller and younger firms in Portugal show higher sensitivity in wages, hours, and employment due to limited access to credit, while Madeira and Salazar (2023) observe that the labor market in Chile's primary sector is the least responsive to monetary shocks. These findings further emphasize the role of firm characteristics in shaping labor market responses to monetary policy across different countries.

We contribute to the empirical literature studying the role of financial frictions on firms, with a focus on investment (Ottonello and Winberry (2020); Jeenas (2023); Cloyne et al. (2023);Ippolito et al. (2018)). While employment is not the primary focus of this literature, the implicit (or explicit) conclusion is that firms more sensitive to monetary policy in terms of investment also tend to grow more overall. We challenge this conclusion by providing evidence that employment and investment responses diverge, with more leveraged firms increasing labor demand while reducing capital intensity. Additionally, we find no significant heterogeneity in sales responses across firms. We replicate the results in Ottonello and Winberry (2020) using annual Compustat data over the same time period and the same estimation strategy. As we combine this evidence with the findings about employment, we conclude that when more leveraged firms, become less capital intensive in response to expansionary monetary shock.

Our paper is organized as follows. Section 1.2 describes the data and empirical specification; Section 1.3 presents empirical evidence; Section 1.4 concludes.

1.2 Data and Methodology

We use annual firm-level data from Compustat to make inferences about the employment and investment response to monetary policy depending on the firm's leverage.

1.2.1 Monetary Policy shocks

We follow the high-frequency approach to the identification of monetary policy shocks by Gurkaynak et al. (2005) and Gorodnichenko and Weber (2016).

The shocks are constructed in two steps. Step one takes the raw jumps in the movement in the federal funds rate implied by the current-month federal funds futures contract in a short window of time (from 15 minutes before the announcement to 45 minutes after the announcement) around the Federal Open Market Committee (FOMC) announcements. The purpose of focusing on a narrow window around the FOMC announcement is that one can be

reasonably certain that no other news caused the change in the futures rates, while the policy decision is already locked, so the movements in the market could not have caused the policy. Second, following Ottonello and Winberry (2020), we aggregate the high-frequency shocks using a weighted moving average of the shocks, so that an announcement at the end of year t_1 is essentially the same as an announcement at the beginning of year t. We provide a detailed explanation of how we construct the shocks as well as a discussion of alternatives in Section A.1 of the Appendix A. Our baseline series begins in January 1990, coinciding with the inception of the Fed Funds futures market, and concludes in December 2007, concentrating on an unbroken spell of conventional monetary policy. We end the sample period before 2008 to avoid the unusual conditions at the onset of the Great Recession and the federal funds rate reaching the zero lower bound, which resulted in little variation in the implied ε_t^m series. We end up with 17 shocks, which are, on average, expansionary. Table 1.1 presents the summary statistics of the shock. To ease interpretation as well as the comparison across methods, we rescale the shocks to have a standard deviation of one and flip the sign so that an increase in the shock indicates an easing of monetary policy.

Table 1.1: Summary statistics of monetary policy shocks

	Raw High Frequency	Smoothed Annual	Smoothed, +, sd 1 Annual
Mean	-0.0185	-0.172	0.559
Median	0	-0.113	0.365
S.D.	0.0855	0.309	1
Min	-0.463	-0.843	-1.075
Max	0.152	0.332	2.732
Observations	164	17	17

Notes: Summary statistics of monetary policy shocks for the period 1/1/1990 to 12/31/2007. "High frequency" shocks are estimated using the event study strategy as in Ottonello and Winberry (2020). "Smoothed" shocks are time aggregated to an annual frequency using the weighted average described in Supplemental Materials A. In the last column, shocks have a flipped sign to ease interpretation and are standardized.

To be clear, ε_t^m should be viewed as an imperfect approximation of the annual structural monetary policy shocks, ε_t^f, which are considered fundamental, unexpected innovations that are independent of other structural disturbances. Since ε_t^f is unobservable, following Stock and Watson (2018), ε_t^m can be used as an instrument for policy rate changes in instrumental

variable (IV) regressions. However, because this essentially amounts to instrumenting one endogenous variable with a single strong instrument, the resulting estimates are nearly identical (up to a scalar factor) to those obtained by using ε_t^m directly as a measure of monetary policy shocks in ordinary least squares (OLS) regressions. In line with the broader literature, we report the main empirical findings using OLS with ε_t^m.

1.2.2 Firm Level data

For the firm-level analysis we obtain information on balance sheet and income statements from the annual Compustat database. Compustat offers a long panel of detailed balance-sheet information for U.S. firms, enabling us to utilize within-firm variation and construct key variables of interest. Our main variable of interest is the change in the log of employment $\Delta \log e_{jt}$, where e_{jt} is number of employees of firm j at the end of the period t. Following Ottonello and Winberry (2020), we study the behavior of capital investment, defined as $\Delta \log k_{jt+1}$, where k_{jt+1} is the book value of the tangible capital stock of firm j at the end of period t, constructed using a perpetual inventory method (Section A.2.1 in the Appendix A). We focus on the responsiveness of firms' capital stocks rather than investment rates, as micro-level investment tends to be lumpy and volatile (Doms and Dunne (1998)). This irregularity makes it challenging to accurately identify systematic responses in investment rates across firms, particularly over longer time horizons. We also consider sales' response as a proxy for the measure of overall firm output.

The main explanatory variable we examine is leverage ℓ_{jt}. More specifically, we measure leverage as a firm's debt-to-asset ratio: a share of the sum of short term and long term debt and in the overall book value of assets. Finally we collect a range of firm-level variables to use as potential controls, including the share of current assets. A shortcoming of Compustat is that it excludes privately held firms and that employment is only available on an annual frequency.

To ensure our results are not influenced by outliers, we winsorize our sample at the top and bottom 0.5% of observations for investment rate, sales growth of more than a 100% or less than a -100%, and leverage is over 1000% . Additional details on sample selection and variable construction are provided in Appendix A, specifically in Sections A.2.2 and A.2.3.

In the baseline analysis, we merge monetary policy shocks to the firm-level data on a calendar year basis (regardless of the fiscal-year definition each firm adopts)[6]. The resulting

[6]As a robustness exercise, we aggregate monetary policy shocks based on fiscal years and merge them to the firm dataset on a fiscal year basis. While potentially being more precise, this specification differs from

underlying unbalanced panel contains 59,111 firm-year observations. Table 1.2 presents basic summary statistics of the sample used in our analysis. Compustat contains only publicly traded firms, thus the median size of the firm in the sample is large, about $ 152 million (in 2017 dollars). The average firm has 700 employees. The right-skewed size distribution of firms motivates the usage of log assets as the relevant measure of size in regressions. The mean leverage ratio is approximately 27% and exhibits considerable variation in the cross-section, with a standard deviation of 37.2%.

Table 1.2: Summary statistics of the firm-level variables in the Compustat sample

	Mean	Median	S.D.	Observations	Corr with leverage
ℓ_{jt}	0.27	0.20	0.37	59,111	
$\Delta \log k_{jt+1}$	0.00	-0.01	0.31	59,111	-0.1046
$\Delta \log e_{jt}$	-0.01	0.00	0.33	57,128	-0.0625
$\Delta \log \frac{k_{jt}}{e_{jt}}$	0.03	0.00	0.41	57,128	-0.0266
$\Delta \log \text{sales}_{jt}$	0.01	0.03	0.38	58,919	-0.0585
Size (mill)	2293.03	152.01	13004.91	59,069	0.0134
Employment	7926.32	700.00	38535.81	57,724	0.0021
Sales (mill)	2134.77	169.28	10984.14	59,030	0.0014

Notes: Summary statistics of firm-level variables for the period 1990-2007. Leverage is measured as total debt to asset, $\Delta \log k_{jt+1}$ is the annual growth in the capital stock, $\Delta \log e_{jt}$ the annual growth in the number of employees, $\Delta \log \frac{k_{jt}}{e_{jt}}$ the annual growth in capital-labor ratio

Larger firms, both by size, sales and employment, tend to have slightly higher leverage. Meanwhile, capital, labor, and capital-labor ratio growth rates are negatively correlated with leverage. 14% of firms in our sample do not hold any debt.

1.2.3 Empirical framework

Our empirical analysis aims to test whether monetary policy's effect on a firm's employment is muted, amplified, or unaffected by firm's leverage. Additionally, we examine other firm-level variables, such as capital and sales, to assess whether the effects of monetary policy on these variables align with the observed labor demand responses.

the baseline by having the monetary policy shock ε_t^m varying across firms. The results are comparable.

We approach this by estimating heterogenous local projections à la Jordà (2005) to capture the dynamic effect of moentary policy. Specifically, we regress the cumulative change in a variable of interest $\Delta_h \log y_{j,t+h} (\equiv \log y_{j,t+h} - \log y_{j,t-1})$ over a given horizon $h \geq 0$ on interaction terms between firms' leverage at the end of period $t-1$ and the monetary policy shock at time t, while controlling for various firm-level characteristics. This allows us to assess the role of the leverage ratio (denoted as $\ell_{j,t-1}$) in shaping firms' responses, both on its own and in combination with other characteristics highlighted in the literature.

We estimate variants of the baseline empirical specification

$$\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}, \tag{1.2.1}$$

where $y_{j,t}$ is firms' employment, capital, capital-labor ratio or sales, $h = 0, 1, \ldots, H$ denotes the horizon at which the relative effect is being estimated, j stands for a firm, and t for a year. $\alpha_{j,h}$ denotes firm j's fixed effect in it's cumulative $h+1-$ year y_j $-$ growth. $\alpha_{s,t,h}$ is a sector s by year t fixed effect for $h+1$-year growth[7]. $\ell_{j,t-1}$ is the firm's leverage ratio (debt-to-asset ratio), $\mathbb{E}_j[\ell_{j,t}]$ the average value of $\ell_{j,t}$ for a given firm j over the sample. $Z_{j,t-1}$ is a vector of lagged firm-level controls, and Y_{t-1} is a vector of aggregate controls. ε_t^m is the measure of the annual monetary policy shock as described in Section .

The main coefficient of interest β^h measures how the semi-elasticity of net hiring in response to a monetary policy shock depends on firms' leverage. For clarity, we scale β^h by 100 to express the results in percentage points. The shock variable, ε_t^m, is standardized by its sample standard deviation, which is approximately 0.309 units, where a positive ε_t^m corresponds to a decrease in the federal funds rate. We also standardize firms' demeaned leverage, $\ell_{j,t-1} - \mathbb{E}j[\ell j, t]$, so that the units represent standard deviations within the sample. As a result $100 \cdot \beta^h$ represents the percentage point difference after h years in the response of net hiring to a 1 standard deviation easing of monetary policy when the firm's prior leverage is 1 standard deviation higher. Positive estimates of β^h would indicate that the increase (decrease) in net hiring prompted by a monetary expansion (contraction) is amplified by firms' leverage.

Our baseline firm controls $Z_{j,t-1}$ include standardized leverage $\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}]$, total assets, sales growth, current assets as a share of total assets, all measured at the end of year $t-1$ to ensure exogeneity with respect to the shock ε_t^m. The extra controls in addition

[7]The sectors s we consider, based on SIC codes, are: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation communications, electric, gas, and sanitary services; wholesale trade; retail trade; and services. We do not include finance, insurance, and real estate, and utilities

to $\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}]$ potentially capture heterogeneity across units that could correlate with their leverage as well as their sensitivity to monetary policy shock. The vector Y_{t-1}, which includes past GDP growth and/or unemployment rate, accounts for potential differences in cyclical sensitivities across units that are not driven by the monetary policy shocks. Since the primary objective is to assess differences in firms' responses to monetary shocks based on their leverage ratios, incorporating sector-time fixed effects, $\alpha_{s,t,h}$, provides a flexible approach to controlling for aggregate time variation. However, this precludes us from measuring the baseline effect of ε_t^m on net hiring or other variables.

We adopt an approach from Ottonello and Winberry (2020) and focus on within-firm variation in leverage, $\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}]$, to ensure that permanent differences across firms do not influence our main results on firms' responsiveness, since firms in the data may be ex-ante heterogeneous in how they react to monetary policy in a way that correlates with their average leverage ratio. For instance, firms in riskier markets may consistently carry higher leverage, making them more exposed to interest rate fluctuations. By demeaning the leverage within firms our estimates capture how a firm's response to monetary policy varies when it has higher or lower leverage than its typical level. We leave the analysis with the level of ℓ_{jt} as a robustness exercise in Appendix A.5.3.

Throughout the analysis, we cluster standard errors in two dimensions, by j and by t, to account for intra-unit and intra-time correlations.

We also apply this specification to a panel of sector-quarter data, where j stands for a sector aggregate financial positions by sector (see Appendix A.4).

1.3 Empirical results

In this section, we demonstrate that more leveraged firms exhibit a stronger labor demand response to monetary policy. Prior research does not provide a straightforward explanation for how leverage affects the transmission of monetary policy to labor demand, since labor cannot serve as collateral. In contrast, the relationship between leverage and capital is more intuitive, with capital frequently acting as a key source of corporate collateral.

Next, we study the behavior of other firm-level variables to shed light on possible mechanisms behind the amplifying role of leverage in the response of labor demand. We show that in contrast to employment, the response of investment to monetary policy is muted for highly leveraged firms (as in Ottonello and Winberry (2020)). Our results are puzzling, revealing that expansionary monetary policy creates a wedge in capital intensity between

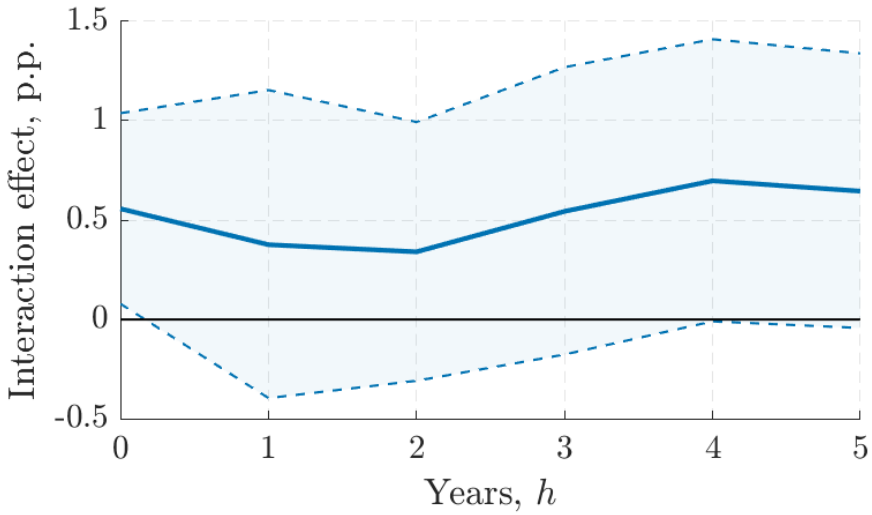
more and less leveraged firms. Overall, we find no evidence of heterogeneous effects on sales.

1.3.1 Employment response to Monetary policy

Figure 1.1 presents the main result of the empirical analysis, showing scaled point estimates for β^h with 90% confidence intervals from the baseline specification (1.2.1). The positive estimates show that firms with higher leverage at the time of an expansionary monetary shock increase their employment relative more compared to the baseline. The effect is significant at the 95% level at the time of the shock, becomes insignificant between years 1 and 3, and returns to significance in year 4.

Within the first year following a one standard deviation cut in interest rates, a firm with leverage 1 standard deviation higher (around 37 percentage points) increases employment by 0.55 percentage points more than the average firm. Despite large standard errors, the point estimates remain high over the five year horizon, indicating a persistent effect. The large standard errors may be due to the small number of monetary shocks in the sample—only 17—forced by Compustat data providing employment information only on an annual basis.

Figure 1.1: Dynamics of heterogeneous net hiring responses to monetary policy



Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variable $y_{j,t+h}$ is employment. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

These findings are also consistent with suggestive evidence at from a quarter-industry panel (NAICS 3-digit), which we present in Section A.4.2 in the Appendix A.4.

Table 1.3 presents the results from estimating the baseline specification (1.2.1) at a time horizon of $h = 0$, which captures the immediate effect within the year of the monetary shock.

Table 1.3: Heterogeneous net hiring responses to monetary policy

	(1)	(2)	(3)	(4)	(5)
leverage × ffr shock	0.00373	0.00396	0.00550**		0.00511*
	(0.00248)	(0.00245)	(0.00258)		(0.00267)
leverage (with mean) × ffr shock				0.00438**	
				(0.00179)	
Observations	51303	51303	49940	49940	42221
R^2	0.247	0.247	0.261	0.261	0.222
Firm controls	no	no	yes	yes	yes
Interaction of leverage with L.GDP	no	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes
Spell of at least 10 years					yes
p-value on main coefficient	0.15	0.13	0.05	0.03	0.07

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is employment. Point estimates and standard errors are reported in log units. Columns 1 and 2 omit the firm-level control variables. Column 1 omits the interaction of past GDP with past leverage. Column 4 reports the result for non-demeaned leverage. The last column restricts the sample to spells of at least 10 years of data on investment (a sample restriction adopted by Ottonello and Winberry (2020)). Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

In Columns 1 and 2, we omit firm-level control variables, while Column 1 also excludes the interaction between past GDP and past leverage. Column 4 presents results using non-demeaned leverage, and the final column restricts the sample to firms with at least 10 years of investment data, a sample restriction similar to that of Ottonello and Winberry (2020). As we incorporate additional controls, the precision of our estimates improves, likely because the controls account for heterogeneity across firms, which may be correlated with both their leverage and their sensitivity to monetary policy shocks, thus reducing noise in our estimates. The point estimates remain within a similar order of magnitude.

Our findings indicate that more leveraged firms respond more strongly to monetary shocks[8]. The most common theoretical explanation for the heightened sensitivity of more leveraged firms to monetary policy is the financial accelerator mechanism, where high leverage is interpreted as a proxy of being financially constrained. Expansionary monetary policy, by raising asset prices, current period revenue and the value of collateral, eases financial constraints. This enables firms that were previously constrained to respond more flexibly to shocks. However, if this financial accelerator effect was driving our results (i.e. expanding firms' borrowing capacity would free the leveraged firm to respond more to the demand shock), we should observe a comparable heterogeneity in the response of firms' investment to expansionary monetary shocks. This reasoning motivates our next subsection, which investigates the heterogeneous response of firms' investment to monetary policy, conditional on leverage.

1.3.2 Investment response to Monetary policy

Figure 1.2 shows the point estimates of β^h, along with 90% confidence intervals, derived from the baseline specification (1.2.1) with firm investment as the dependent variable. The point estimate differences turn negative at the time of the shock (Table A.2 in Appendix A.3) and become statistically significant at the 95% level one year later.

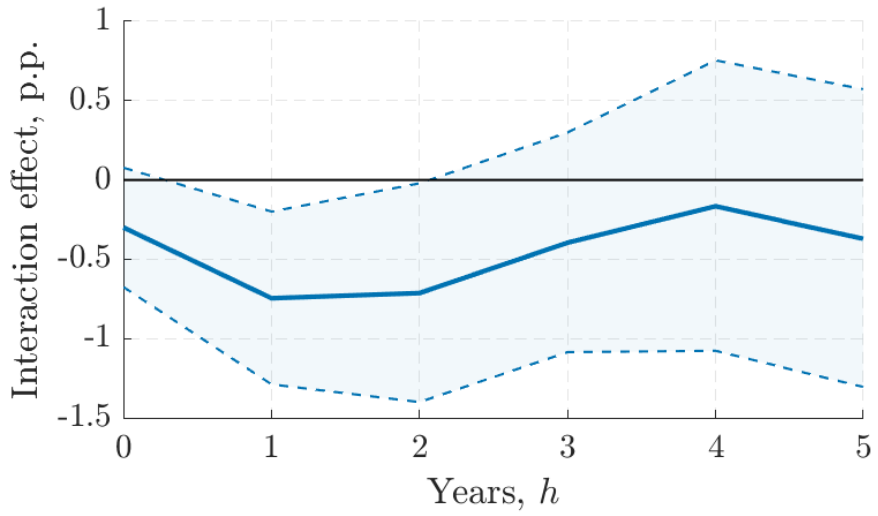
In contrast to our analysis of employment, the behavior of investment suggests that more leveraged firms are less responsive to monetary policy. These results replicate those of Ottonello and Winberry (2020)[9]. Ottonello and Winberry (2020) argue that after a positive monetary shock raises investment demand across the board, leveraged firms respond less than they would want as they bump against their financial constraints. While the financial accelerator channel is present and pushes in the opposite direction, it is dominated by the direct effect of constraints. Overall, the behavior of investment is inconsistent with the hypothesis that leverage amplifies the response of employment through the financial accelerator channel.

Aligned with the response of aggregate economic activity, as estimated by Gertler and Karadi (2015), differences in fixed capital accumulation take time to materialize. The largest differences, observed between one and two years after the shock, indicate that a 37 percentage points higher leverage ratio predicts approximately 0.55 percentage points lower cumulative

[8]Our baseline specification yields results that are consistent with the findings of Bahaj et al. (2022), who show that employment at younger, more-leveraged firms is the most sensitive to monetary policy shocks, based on micro-data from private and public UK firms.

[9]They use quarterly Compustat data over the same time period and the same estimation strategy.

Figure 1.2: Dynamics of heterogeneous investment responses to monetary policy



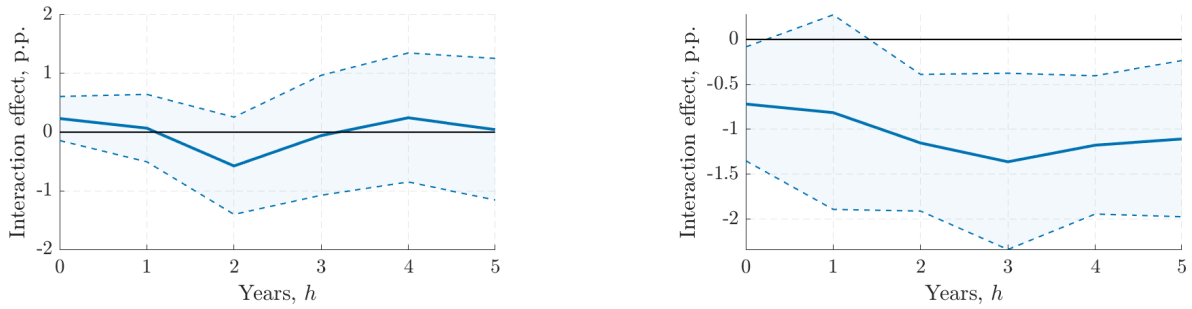
Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variable $y_{j,t+h}$ is physical capital. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

capital growth following a one standard deviation monetary policy shock. Afterward, the differences begin to gradually dissipate.[10] The analysis of investment on the sector level is consistent with the firm-level heterogeneity (see Appendix A.4.2)

1.3.3 Additional analysis for sales and capital-labor ratio

Figure 1.3 (a) presents the results of the baseline analysis, where we use the log-change in the firm's sales as the a proxy for the firm's total output. The differential response of sales to a monetary policy shock is zero on average over a 5-year horizon, with a temporary shift from positive to negative midway through the period. This suggests that leverage actually does not significantly impact whether a firm grows more or less overall after a monetary policy shock. Instead, heterogeneity in leverage is primarily affecting the firms' mode of production.

Figure 1.3: Dynamics of heterogeneous sales' and capital-labor ratio's responses to monetary policy



(a) Sales (b) Capital-Labor ratio

Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variable $y_{j,t+h}$ for panel (a) is sales, for panel (b) – Capital-Labor ratio. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

Figure 1.3 (b) illustrates this clearly. Within the first year following a one standard deviation cut in interest rates, a firm with leverage 1 standard deviation higher (about 37 percentage points) reduces its capital intensity (capital-labor ratio) by 0.7 percentage points. This effect persists and reaches a maximum decline of 1.5 percentage points three years after the shock.

[10]The magnitude of this effect aligns with the findings of Durante et al. (2022), though it is opposite in sign. They use annual firm-level data from four European countries.

Notably, the capital-labor ratio does not recover within the 5-year period. The immediate effects on firms' sales and capital-labor ratios are reported in Tables A.3 and A.4, respectively, in Appendix A.3.

1.3.4 Robustness

Appendix A.5.3 presents three sets of additional empirical results that serve as robustness checks for our main findings. The first set addresses alternative definitions of monetary policy shocks. Table A.7 shows that the results remain robust when controlling for the information channel of monetary policy, using Greenbook forecast revisions following Miranda-Agrippino and Ricco (2021). Additional specifications using alternative monetary policy shock series yield similar conclusions and are discussed in the same Section A.5.1.

The second set examines robustness with respect to firm-level heterogeneity. These specifications allow the monetary policy shock to interact with other firm characteristics such as size, sales growth, and the share of current assets in total assets (see Tables in Section A.5.2).

The third set of results connects our analysis to existing literature. We demonstrate that our findings remain consistent when using alternative measures of firms' financial positions—such as distance to default (as in Ottonello2020, Figure A.5), firm liquidity (as in Jeenas2023, Figure A.6), and firm age (as in Cloyne2023, Figure A.8).

1.4 Conclusion

In conclusion, we show that firm leverage systematically shapes the response of input choices to monetary policy shocks: more leveraged firms adjust primarily through labor rather than capital. Contrary to financial accelerator-type mechanisms, we find little evidence that leverage amplifies investment responses or overall output. Instead, our results highlight leverage as a key determinant of capital-labor substitution. Understanding the underlying mechanisms behind this reallocation—and its aggregate implications—requires further theoretical work.

CHAPTER 2

A New Keynesian Model with Capital-Labor Substitution under Financial Constraints [1]

2.1 Introduction

Monetary policy is one of the central tools governments use to stabilize the business cycle. Interest rate adjustments affect a wide range of economic decisions—from household consumption to business investment and labor demand. A large body of economic research studies how monetary shocks influence firm behavior, typically under the assumption that companies respond by scaling all inputs—capital, labor, and output—proportionally. These assumptions are often embedded in standard macroeconomic models, which rely on fixed production technologies, such as Cobb-Douglas, and uniform price-setting behavior across firms. However, growing empirical evidence suggests that firm responses to monetary easing are far more heterogeneous, especially when financial frictions limit access to external funding.

Our empirical analysis in Chapter 1, along with related studies, finds that highly leveraged firms tend to expand employment more than capital investment following monetary easing, while keeping sales relatively flat. This pattern indicates a reallocation of inputs—substituting labor for capital—rather than a uniform expansion of production. Understanding this asymmetry is critical for evaluating the effectiveness of monetary policy in environments where financial constraints vary widely across firms.

We propose that this asymmetry arises from a strong aggregate demand channel interacting with firm-level financial frictions. When monetary policy loosens, aggregate demand rises, boosting demand for firm output. However, for firms with limited financial flexibility, expanding capital is difficult. In response, these firms meet demand by increasing labor in-

[1] joint with Tereza Ranošová

put instead, lowering their capital–labor ratio. This reallocation amplifies the labor response to monetary policy but dampens the investment response. Our mechanism contrasts with the conventional view, in which capital, labor, and output all move in the same direction in response to a change in firms' borrowing capacity (Jungherr et al. (2022); Ippolito et al. (2018); González et al. (2024)).

To formalize this mechanism and explore its implications for the broader economy, we develop a New Keynesian model with heterogeneous firms and flexible input choices under financial constraints. Firms differ in their leverage and face occasionally binding collateral and dividend payout constraints, modeled using penalty functions as in Jermann and Quadrini (2012) and Brzoza-Brzezina et al. (2015). Firms finance capital and labor using both internal and external funds, and sell intermediate goods to retail firms that operate under nominal rigidities, generating standard New Keynesian price dynamics.

Our framework departs from standard models in two key ways. First, we replace Cobb-Douglas production with a constant elasticity of substitution (CES) technology, allowing for variation in capital–labor substitution in response to shocks. This feature is critical for replicating the observed divergence in input responses. Second, we relax output price symmetry across wholesale firms, introducing differentiated products and downstream preferences for variety. These changes ensure that aggregate demand shocks affect both constrained and unconstrained firms, allowing substitution dynamics to propagate throughout the economy.

We calibrate the model to match the empirical responses observed in Chapter 1. The model successfully reproduces the asymmetric pattern: more leveraged firms increase employment while cutting back on investment after monetary easing, with output effects remaining modest. At the aggregate level, financial frictions dampen the response of capital and prices, while employment adjusts more slowly—initially muted, then amplified over time as firms reallocate production toward labor. These dynamics are absent in standard models that enforce fixed input shares and pricing structures.

To evaluate the importance of our modeling innovations, we compare our baseline with a benchmark model featuring Cobb-Douglas production and symmetric pricing. While both frameworks produce qualitatively similar aggregate outcomes, the benchmark underestimates the role of leverage in shaping firm-level heterogeneity and overstates the persistence of output effects. These results underscore the need for realistic production and pricing assumptions when studying monetary policy in financially constrained economies.

Our contribution is threefold. First, we introduce a tractable general equilibrium model that embeds firm-level heterogeneity in leverage and allows for substitution between capital

and labor. Second, we demonstrate that the model can quantitatively match empirically observed input asymmetries in firm responses to monetary policy without requiring large differences in productivity or demand elasticities. Third, we show that these micro-level distortions alter aggregate dynamics in important ways—particularly in environments where leverage is elevated and monetary policy aims to stimulate real activity.

This paper contributes to a growing literature that incorporates financial frictions and firm heterogeneity into macroeconomic models (Ottonello and Winberry (2020); Ippolito et al. (2018); Drechsel (2023); Jeenas (2023)). While previous work has emphasized the impact of financial constraints on investment, our framework highlights the importance of accounting for flexible input substitution and reallocation in shaping firms' responses to monetary policy. Additionally, it complements work on household heterogeneity in New Keynesian settings (McKay et al. (2016); Kaplan et al. (2018); Auclert (2019); Wong et al. (2019)) by shifting the focus to the production side, offering new insight into how financial constraints affect firms' labor demand and production choices, and ultimately, macroeconomic policy transmission.

Our paper is organized as follows. Section 2.2 presents the model and calibration; Section 2.3 uses the model to study the monetary transmission mechanism; Section 2.4 concludes.

2.2 Model

In this section, we build a mode that allows us to explain the empirical patterns observed in Section 1.3 of Chapter 1. We consider a New Keynesian model with two types of firms that face dividend and collateral constraints and are hit by idiosyncratic shocks of opposite signs to their debt at the beginning of the period. The model comprises three parts: a production block that captures firms' heterogeneous responses to monetary policy, a New Keynesian block that produces the Phillips curve, and a representative household block that completes the framework.

2.2.1 Production block

A continuum of size 1 of wholesale firms produces intermediate goods. Within the continuum are two types of firms, $j \in A, B$. Firms with $j = A$ are hit with v_t, an unanticipated transitory shock to their debt stock, while $j = B$ denotes firms that are hit with $-{v_t}^2$. The measure of type-A firms is 0.5. All intermediate producers operate the technology

[2]Mechanically, the shock to debt stock allows us to generate heterogeneity in leverage.

$y_t^j(i) = f(k_t^j(i), n_t^j(i))$, where is $k_t^j(i)$ the input of pre-determined capital, $n_t^j(i)$ the input of labor. We will discuss a choice of production function later in the paper.

In period t firms sell the intermediate good at nominal price P_t^j, while P_t is the nominal price of the final good, taking both as given. The firm's revenue in real terms is defined as

$$p_t^j f(k_t^j(i), n_t^j(i)),$$

where $p_t^j = \frac{P_t^j}{P_t}$ is the real price of the intermediate good of type-j firm.

Firms can borrow using one-term debt contracts, up to a constraint. Specifically, a firm faces a borrowing constraint, which states that the market value of its debt outstanding entering the upcoming period must be less than a fraction θ of the market value of its capital stock brought into that period. Firms are unable to issue equity and must pay a certain amount of dividends to their shareholders. Specifically, the minimum amount of dividends paid to shareholders has to be at least a fraction ω of the payout target (steady-state level of $d_t^j(i)$). Interest payments are tax-deductible, introducing a tax advantage of debt.

The decision problem of a firm is to pick a dividend $d_t^j(i)$, capital $k_{t+1}^j(i)$, labor $n_t^j(i)$ and debt $b_{t+1}^j(i)$ sequences to maximize the expected stream of dividends, discounted at its owner's discount factor $m_{t,t+1}$. State variables are $k_t^j(i)$ and $b_t^j(i)$(endogenous), and v_t^j (exogenous).

$$\max_{d_t^j(i), n_t^j(i), k_{t+1}^j(i), b_{t+1}^j(i)} \mathbb{E}_0 \sum_{t=0}^{\infty} m_{0,t} d_t^j(i) \tag{2.2.1}$$

subject to

$$\begin{aligned} d_t^j(i) = {} & p_t^j y(k_t^j(i), n_t^j(i)) - w_t n_t^j(i) - Q_t[k_{t+1}^j(i) - (1-\delta)k_t^j(i)] \\ & - \frac{(1+v_t^j)b_t^j(i)}{1+\pi_t} + \frac{b_{t+1}^j(i)}{R_t} && (2.2.2) \\ & \omega \overline{d} \leq d_t^j(i) && (2.2.3) \\ & b_{t+1}^j(i) \leq \theta \mathbb{E}_t Q_{t+1}(1-\delta)k_{t+1}^j(i) && (2.2.4) \\ & y_t^j(i) = f(k_t^j(i), n_t^j(i)) && (2.2.5) \\ & R_t = 1 + (1-\tau)r_t^n, && (2.2.6) \end{aligned}$$

where $\pi_t \equiv \frac{P_t}{P_{t-1}}$ is inflation rate, and r_t^n - the nominal one-period risk-free rate, w_t is the real wage and Q_t is the real price of a unit of capital (all common across firms). A firm's capital

depreciates at rate $\delta \in (0,1)$.

2.2.2 New Keynesian block

Retail firms and Final Good Producer There is a unit mass of retail firms, each with a constant returns to scale production function that transforms bundled wholesale goods into intermediate retail goods:

$$y_t(k) = g(x_t^A, x_t^B)$$

with x_t^A, x_t^B the amount of intermediate goods from wholesale producers employed as input by retailer k in period t. The retailers purchase from the two types of production firms operating in a competitive market for the nominal prices P_t^A, P_t^B, and sell their production for price $p_t(k)$. They operate in a monopolistic competition and take the demand curve for their retail good as a function of $p_t(k)$ as given. In setting their prices, the retailers face Rotemberg (1982) adjustment costs $\frac{\varphi_p}{2}\left(\frac{p_t(k)}{p_{t-1}(k)} - \overline{pi}\right)^2 y_t$, Here, $\overline{\pi} > 0$ is a parameter that denotes the steady state gross inflation rate, thus effectively allowing for "price indexing" and a non-unitary steady state gross inflation rate. y_t is the aggregate production of the final good.

The assumption of constant returns to scale ensures that the choice can be separated into cost minimizing combination of inputs and a profit maximization choice of output and price. Thus we can write the real profit of the retailer as

$$\frac{p_t(k)}{P_t} y_t(k) - mc(p_t^A, p_t^B) y_t(k),$$

where $mc(p_t^A, p_t^B)$ is marginal cost of retail goods production.

The final good is produced by a perfectly competitive final good producer who takes the prices of the final good and the retail goods as given. It has a constant elasticity of substitution production function, combining the retail goods into the final good with elasticity of substitution η

$$y_t = \left(\int y_t(k)^{\frac{1}{\eta}}\, dk\right)^{\eta}, \tag{2.2.7}$$

η defines nominal price markup.

Optimization by the final goods producers gives rise to the demand for retail good $k \in [0,1]$, of

$$y_t(k) = \left(\frac{p_t(k)}{P_t}\right)^{-\frac{\eta}{1-\eta}} y_t.$$

The combination of the isoelastic demand curve, the quadratic price adjustment costs, linear production function of retailers and initial price symmetry gives rise to a New Keynesian Phillips Curve, with $\hat{\pi}_t \equiv \log(\pi_t) - \log(\pi_{SS})$, of:

$$\hat{\pi}_t = -\kappa_p \log\left(\frac{\mathcal{M}_t}{\overline{\mathcal{M}}}\right) + \beta\hat{\pi}_{t+1} \tag{2.2.8}$$

which we consider in the log-linearized form around a steady state with $\overline{\pi}$, and $\overline{\mathfrak{M}} = \eta$, as common in the literature. $\kappa_p \equiv \frac{1}{(\eta-1)\varphi_p\overline{\pi}^2}$ is the slope of the Phillips curve and $\mathcal{M}_t = 1/mc_t$.

Capital production There is a representative capital goods producer who produces new capital goods with the production technology $\Phi(\frac{I_t}{K_t})K_t$, where I_t are the units of the final good used in capital production, K_t is aggregate capital in place at the beginning of t, and $\Phi(\iota) = \frac{\delta^{\varrho}}{1-\varrho}\iota^{1-\varrho} - \delta\frac{\varrho}{1-\varrho}$, with $\varrho \in [0,1)$ a parameter. The capital goods producer chooses final goods spent on capital goods production, I_t, to maximize profits

$$Q_t\Phi(\frac{I_t}{K_t})K_t - I_t \tag{2.2.9}$$

therefore, in equilibrium the relative capital price Q_t equals:

$$Q_t = \left[\Phi'(\frac{I_t}{K_t})\right]^{-1} = \left(\frac{I_t/K_t}{\delta}\right)^{\varrho} \tag{2.2.10}$$

I_t implicitly determined by

$$K_{t+1} = \Phi(\frac{I_t}{K_t})K_t + (1-\delta)K_t. \tag{2.2.11}$$

Government and Monetary Authority I combine the conduct of fiscal and monetary policy under the hood of the government.

The government faces the budget constraint:

$$T_t = \frac{B_t}{1 + r_t^n(1+\tau)} - \frac{B_t}{1 + r_t^n}$$

T_t denotes lump sum taxes raised on the household to ensure that the budget constraint is satisfied.
The monetary authority sets the nominal one-period risk-free rate r_t^n between $t-1$ and t

following a standard Taylor rule, in nonlinear form, with

$$\frac{1+\frac{r_t^n}{1+\overline{r^n}}}{1+\frac{\overline{r^n}}{1+\overline{r^n}}} = \left(\frac{1+\frac{r_{t-1}^n}{1+\overline{r^n}}}{1+\frac{\overline{r^n}}{1+\overline{r^n}}}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\overline{\pi}}\right)^{\nu_1} \left(\frac{\frac{y_t}{y_t^*}}{\frac{y_{t-1}}{y_{t-1}^*}}\right)^{\nu_2}\right]^{1-\rho_R} \xi_t, \tag{2.2.12}$$

where ρ_R, ν_1, and ν_2 are parameters and $\xi_t \sim N(0, \sigma_\xi)$

2.2.3 Representative Household and Market clearing

There is a continuum of homogeneous households maximizing the expected lifetime utility $E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_t)$, where $U(C_t, L_t) = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{L_t^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}}$, with C_t is consumption, L_t is labor, and β a discount factor. Households are the owners (shareholders) of firms. In addition to equity shares of both firms, they hold one-period bonds issued by firms. The household's recursive budget constraint is

$$\begin{aligned} w_t L_t + \frac{b_t}{\pi_t} + \int s_t(i)(d_t(i) + p_t^s(i))di + = \\ \frac{b_{t+1}}{1+r_t^n} + \int s_{t+1} p_t^s(i)di + T_t + C_t + \Xi_t^r, \end{aligned} \tag{2.2.13}$$

where w_t is the real wage, b_t the amount of one period bonds in real terms ($b_t = \frac{B_t}{P_{t-1}}$ and $b_{t+1} = \frac{B_{t+1}}{P_t}$), r_t^n is the nominal interest rate and $\pi_t = \frac{P_t}{P_{t-1}}$ inflation. $s_t(i)$ is the equity share of firm i, $d_t(i)$ is equity payout received from owning shares of firm i and $p_t^s(i)$ is the real market price of firm i shares. $T_t(i)$ are lump sum taxes financing the tax benefit of debt to firms and Ξ_t^r are the profits of the retail and capital goods producer.

We impose a standard set of market clearing conditions.

$$\text{Final good market clearing } : y_t = c_t + I_t \tag{2.2.14}$$

$$\text{Capital market clearing } K_t = \int k_t(i)di = 0.5(k_t^1 + k_t^2) \tag{2.2.15}$$

$$\text{Labor market clearing } L_t = \int n_t(i)di = 0.5(n_t^1 + n_t^2) \tag{2.2.16}$$

$$\text{Debt market clearing } B_t = \int b_t(i)di = 0.5(b_t^1 + b_t^2) \tag{2.2.17}$$

2.2.4 Collateral and dividend constraints

Inequality constraints generally prevent one to use standard local solution methods. A possible way of incorporating a borrowing constraint (2.2.4) and a dividend constraint (2.2.3) is to assume that they are eternally binding (EBC)(Jermann and Quadrini (2012)). This is legitimate if impatient households' discount factor is low and shocks hitting the economy are sufficiently small. However, that set-up does not produce variation in the leverage ratio. Even more importantly, the EBC assumption makes the discussion about switching between constraint and unconstrainted states and its impact on firm behavior irrelevant.

To subvert this problem we will follow the approach of Brzoza-Brzezina et al. (2015) and approximate the occasionally binding constraints with penalty functions that subtract from the firms dividends each period. Specifically, we replace each constraint with an exponential cost function:

$$\Psi_t^{dj}(i) = \frac{1}{\chi_d} \exp\left(\chi_d \left(\omega \overline{d^j(i)} - d_t^j(i)\right)\right), \tag{2.2.18}$$

$$\Psi_t^{bj}(i) = \frac{1}{\chi_b} \exp\left(\chi_b \left(b_{t+1}^j(i) - \theta \mathbb{E}_t \left[Q_{t+1}(1-\delta) k_{t+1}^j(i)\right]\right)\right). \tag{2.2.19}$$

If $\chi_d, \chi_b \to \infty$, the penalty function collapses to the inequality constraint.

2.2.5 How do financial constraints affect the demand for capital and labor?

We have presented our empirical results, highlighting the key observation that leverage amplifies the impact of monetary policy on firm employment, while leveraged firms tend to become relatively less capital-intensive when monetary policy loosens. In this section, we discuss under what conditions our model reproduces our empirical findings. We will start with a discussion of the role of financial constraints in the investment channel of monetary policy transmission and then proceed to implications for the firm's labor demand.

Investment channel of Monetary policy: The investment channel of monetary policy operates through two potential mechanisms. On the one hand, financial frictions generate an upward-sloping marginal cost curve for investment, with the slope steeper for firms closer to hitting the constraint. As monetary policy motivates increases investment demand, the firms operating on a steep portion of the marginal cost (supply) curve invest less. On the other hand, monetary policy can alleviate these constraints by boosting cash flows or improving collateral values, effectively flattening the marginal cost curve and amplifying the

investment response of firms. This latter view aligns with the financial accelerator theory, which posits that firms with tighter financial conditions are more responsive to changes in monetary policy. Although Ottonello and Winberry (2020) provides a detailed discussion of the conditions under which each mechanism prevails, we do not delve into this debate as it is not the primary focus of our paper. Nevertheless, Ottonello and Winberry (2020) finds a more muted investment response (which we replicate), suggesting that the first mechanism—financial frictions-steeper marginal cost curve—plays a dominant role. In our model, we impose two key constraints—dividend distribution and collateral—which influence firms' investment decisions. We calibrate the model such that the firm's investment responses align with the data, and firms with higher leverage expand their investment less after expansionary monetary shock.

Labor demand response to monetary policy: Our empirical results suggest that, contrary to capital, leveraged firms' labor demand reacts more strongly to monetary policy. Here, we show that whether employment follows capital depends crucially on the parametrization of the supply side of the model, specifically the choice of f and g.

A common approach to defining the revenue function (2.2.1) in the wholesale firms' problem, in a setting with multiple firms, treats all firms as price takers facing the same output price, with production functions following a Cobb-Douglas form:

$$p_t^j f(k_t^j(i), n_t^j(i)) = p_t \left(k_t^j(i)^\alpha n_t^j(i)^{1-\alpha}\right)^\nu,$$

where α represents the capital share and ν denotes returns to scale (this is exactly the function forms chosen by Ottonello and Winberry (2020)). This framework implicitly makes two key assumptions. First, the elasticity of substitution between capital and labor is equal to one. Second, the output of different firms is perfectly substitutable ($g(x_t^A, x_t^B) = 0.5x_t^A + 0.5x_t^B$ and $p^A = p^B$ always holds in equilibrium). Then, each firm's labor demand function is as follows:

$$n_t^j(i) = \left(p_t \frac{\nu(1-\alpha)}{w_t} k_t^j(i)^{\alpha\nu}\right)^{\frac{1}{1-\nu(1-\alpha)}}.$$

For any value of and ν, $\frac{\partial n}{\partial k}$ is positive, and nothing else in the labor demand function is firm-specific. In other words, across firms, labor always follows capital. In this context, if a firm's investment response to an expansionary monetary shock is muted, its labor response must also be muted, a behavior inconsistent with our empirical results.

We propose to relax both assumptions. First, we allow capital and labor to be more

substitutable in production. This frees the paths of capital and labor from being tied together by technology. Second, we allow the intermediate outputs of wholesale firms A and B to be imperfectly substitutable in the production of the retailer's intermediate goods. Relaxing this second assumption ensures that the aggregate demand channel of monetary policy affects all firms. Expansionary monetary policy shocks increase demand for the consumption good, increasing demand for all retailer varieties. In turn, retailer firms demand more inputs from wholesale firms. If the output of firms A and B is not perfectly substitutable, retailers exert demand pressure on both firms to increase their output, with prices adjusting in equilibrium. Since more leveraged firms face limitations on how much capital they can raise to meet this increased demand, they are strongly motivated to expand output through increased labor demand instead. If the output of firms A and B was perfectly substitutable, the constrained firms could simply slack off, with the unconstrained firms taking over the market share.

The following analytical framework captures the intution above. First, we set

$$f(k_t^j(i), n_t^j(i)) = \left(\alpha k_t^j(i)^{-\rho} + (1-\alpha) n_t^j(i)^{-\rho}\right)^{-\frac{\nu}{\rho}},$$

where ρ governs the elasticity of substitution, with elasticity $= \frac{1}{1+\rho}$. If $\rho = 0$, the production function collapses to Cobb-Douglas.

Second, the production function for the retail firm is given by:

$$g(x_t^A, x_t^B) = \left(x_t^{A\,\frac{\kappa-1}{\kappa}} + x_t^{B\,\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{\kappa-1}},$$

where $\kappa > 1$ is the substitution parameter. Notice, if $\kappa = \infty$, the price of both firms is the same.

Under this upstream-downstream production structure, the equilibrium labor demand for a firm i of type j is given by:

$$n_t^j(i) = \left(\frac{\nu(1-\alpha)}{w_t}\right)^{\frac{1}{\rho+1}} \left(\widetilde{p}_t y_t^j(i)\right)^{\left(\frac{\nu+\rho}{\rho} - \frac{1}{\kappa}\right)\frac{1}{1+\rho}} y_t(k)^{\frac{1}{\kappa(1+\rho)}}, \quad j = A, B,$$

where $\widetilde{p_t} = \left(p_t^{A\,1-\kappa} + p_t^{B\,1-\kappa}\right)^{\frac{1}{1-\kappa}}$ represents the aggregate price index for wholesale intermediary goods. It's also worth noting that $\widetilde{p_t}$ is the marginal cost $mc(p_t^A, p_t^B)$ in the retail firms' profit maximization problem.

A necessary condition for $\frac{\partial n}{\partial k}$ and $\frac{\partial n}{\partial y}$ to be negative is for $\frac{\nu+\rho}{\nu} - \frac{1}{\kappa} < 0$. This condition is more likely to hold if capital and labor are substitutable while x^A and x^B are not.

2.2.6 Calibration

We calibrate the model to annual frequency and take parameters from the literature. The exact values of the calibrated parameters are presented in Table 2.1. We set the discount factor to $\beta = 0.938$, implying an annual risk-free rate of 6.6%. We set household's elasticity of intertemporal substitution σ to 1, and labor supply elasticity to $\epsilon = 0.44$. On the production side, we set the capital share to $\alpha = 0.22$, and the returns to scale parameter to $\nu = 0.8$. Capital depreciates at a rate $\delta = 0.12$ annually. We choose the steady state markup of retailers $\eta = 1.125$. We set $\varrho = 0.25$ in the capital production function, matching the curvature of 4 from Bernanke et al. (1996). We consider a tax rate of $\tau = 0.35$ (Hennessy and Whited (2005)) which is an approximation of the statutory corporate tax rate relative to personal tax rates in the U.S. We choose the limit on the loan-to-value ratio $\theta = 0.17$ and the lower bound of dividend constraint $\omega = 0.7$. We set the price adjustment cost parameter at $\phi_p = 700$, which implies that the Phillips Curve slope is equal to 0.01, similar to Hazell et al. (2022) estimates. The coefficient on inflation in the Taylor rule is $\nu_1 = 2.5$, while keeping $\nu_2 = \nu_3 = 0$ for simplicity. Finally, we choose the elasticity of substitution between capital and labor at $\rho = -0.44$ (as in von Brasch et al. (2023)) and set $\kappa = 1.04$, implying a strong demand for inputs variety from retailer firms.

As discussed in the Brzoza-Brzezina et al. (2015), there is a trade-off between the amount of penalty function curvature and the feasibility of solving the model using perturbation techniques. Since one of our goals is to investigate the ability of the financial constraints and generalized supply side to explain the patterns observed in the data, we opt for a moderate value of $\chi = 90$. In the same spirit, we set the standard deviation of a monetary shock to be $\sigma_{\epsilon^m} = 10^{-6}$, and the standard deviation of debt shock $\sigma_v = 10^{-2}$, so that debt shocks are the primary generator of variation in how binding financial constraints are.

2.3 Monetary policy analysis

2.3.1 Aggregate Response to Monetary Policy

Figure 2.1 plots the responses of key aggregate variables to an expansionary monetary policy shock. The shock lowers the nominal interest rate and, because prices are sticky, also the real interest rate. A lower real interest rate stimulates investment demand by shifting out the marginal benefit of investment. It also stimulates consumption demand from the household due to the standard intertemporal substitution channel. The higher aggregate

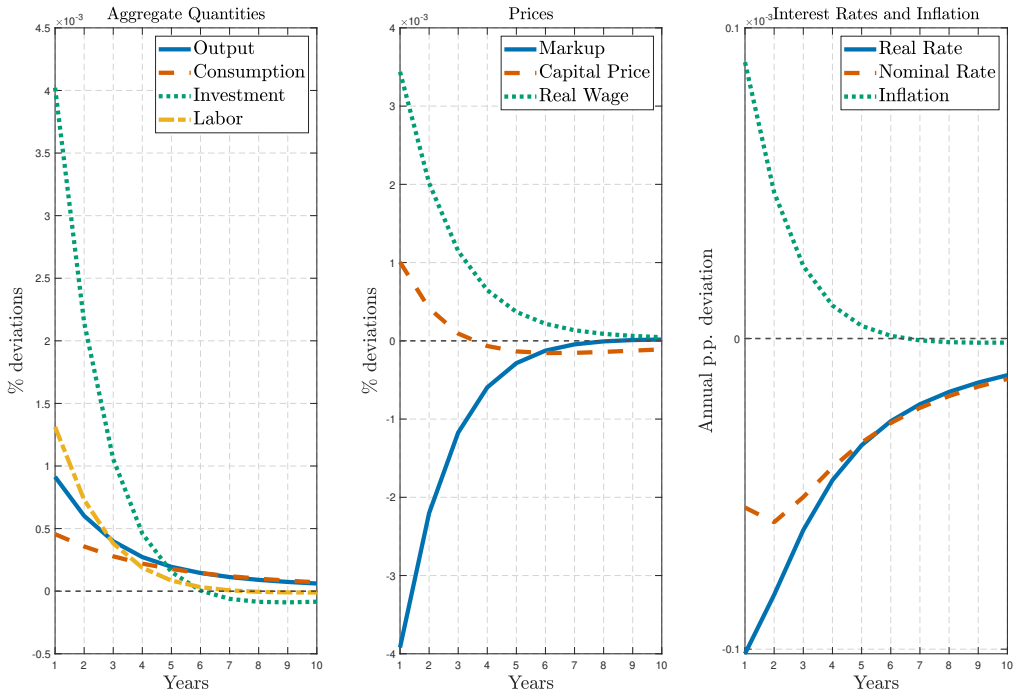
Table 2.1: Calibrated parameters.

Parameter	Value	Comment on parameterization
(a) Structural parameters		
σ	1	Household intertemporal elasticity
α	0.22	Capital share of output
ϵ	0.44	Elasticity of labor supply
ν	0.8	Decreasing returns to scale
ρ	-0.44	Substitution parameter, intermediary production function
κ	1.04	Substitution parameter, retail production function
δ	0.12	Depreciation rate of 12% per year
β	0.938	Target steady state annual interest rate of 6.6%
ϱ	0.25	Elasticity of capital prices to aggregate investment
η	1.125	Steady state markup
τ	0.35	Corporate tax rate
ω	0.7	Dividend constraint parameter
θ	0.17	Collateral constraint parameter
χ	90	Penalty function parameter
(b) New Keynesian Parameters		
φ_p	700	Price adjustment coefficient, $\kappa_p = 0.01$
ρ_R	0.795	Interest rate auto-correlation
ν_1	2.5	Taylor rule coefficient
(c) Shocks		
σ_{ε^m}	10^{-6}	S.D. of Monetary shocks
ρ_ε	0.4	Persistence of monetary policy shock
σ_v	10^{-2}	S.D. of debt stock shock
ρ_v	0	Persistence of debt stock shock

demand for goods changes other prices in the economy, third subfigure "Prices" of Figure 2.1. If re-scaled to a monetary shock of $\varepsilon^m = -0.0025$ commonly used in the literature, the investment increases by approximately 10%, consumption increases by 1.5%, labor demand increases by 3.5%, and output increases by 2.1%. These magnitudes are broadly in line with the annualised peak effects of monetary policy shocks in Ottonello and Winberry (2020); they find that investment increases by approximately 6%, consumption increases by 1.6%, and output increases by 2%.[3]

[3]Ottonello and Winberry (2020) do not provide results for change in labor demand.

Figure 2.1: Aggregate responses to expansionary monetary shock.

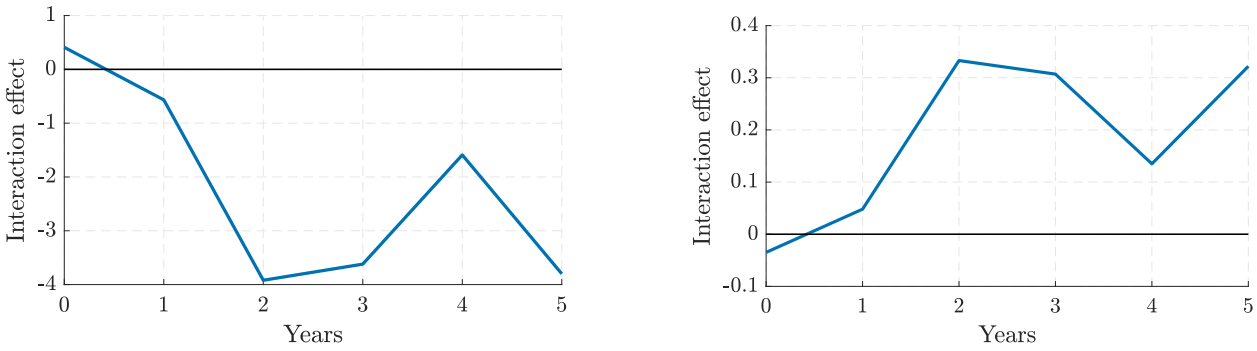


Notes: Aggregate impulse responses to a $\varepsilon^m = -10^{-6}$ innovation to the Taylor rule which decays at a rate $\rho_\varepsilon = 0.4$.

2.3.2 Heterogeneous Responses to Monetary Policy

To compare our model with the empirical results, we simulate a panel of economies with two firms responding to a monetary shock and estimate our empirical specification (1.2.1) using the simulated data[4]: $\Delta \log y_{j,t+h} = \alpha_j + \alpha_t + \beta^h(\ell_{j,t-1} - \overline{\ell}_j)\varepsilon_t^m + \epsilon_{j,t+h}$. We assume that the high-frequency shocks ε that we measure in the data are the innovations to the Taylor rule in the model. Figure 2.3.2 illustrate that the differential responses of labor, and the capital-labor ratio, exhibit persistence in the model and align broadly with the empiprical results. More leveraged firms become less capital-intensive while increasing employment more than more leveraged firms. Notes: Estimating equation $\Delta_h \log y_{j,t+h} =$

Figure 2.2: Dynamics of labor demand's and capital-labor ratio's differential responses to monetary shocks in the model



(a) Capital-Labor ratio (b) Labor Demand

Notes: Estimating equation$\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \epsilon_{j,h,t+h}$ for $h = \overline{0,5}$ on simulated data without controls. The dependent variables $y_{j,t+h}$ are (a) Capital-Labor ratio, (b) labor Demand. The standard errors are clustered at the firm and economy levels. A panel of 100 economies with 900 periods. y-axis values are in units of standard deviation of σ_{ε^m}

$\alpha_{j,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \epsilon_{j,h,t+h}$ for $h = \overline{0,5}$ on simulated data without controls. The dependent variable $y_{j,t+h}$ is firm output. The standard errors are clustered at the firm and economy levels.

As in Ottonello and Winberry (2020)), more leveraged firms invest less in capital after an expansionary monetary policy shock. Leveraged firms produce slightly less, but the effect is significantly muted compared to the response of capital (see Figure B.1 in Appendix ??),

[4]Unlike in empirical specification we do not use vector of control variables $Z_{j,t-1}$. We also use time time fixed effects rather than sector-time fixed because our model does not contain multiple sectors

consistent with our empirical results showing no significant heterogenous responses in sales. This is because firms compensate for the lack of capital by increasing labor demand in response to the aggregate demand pressure. Overall, the primary role of heterogeneity in financial constraints across firms is in determining the mode of production.

2.3.3 Aggregate implications of Financial Constraints

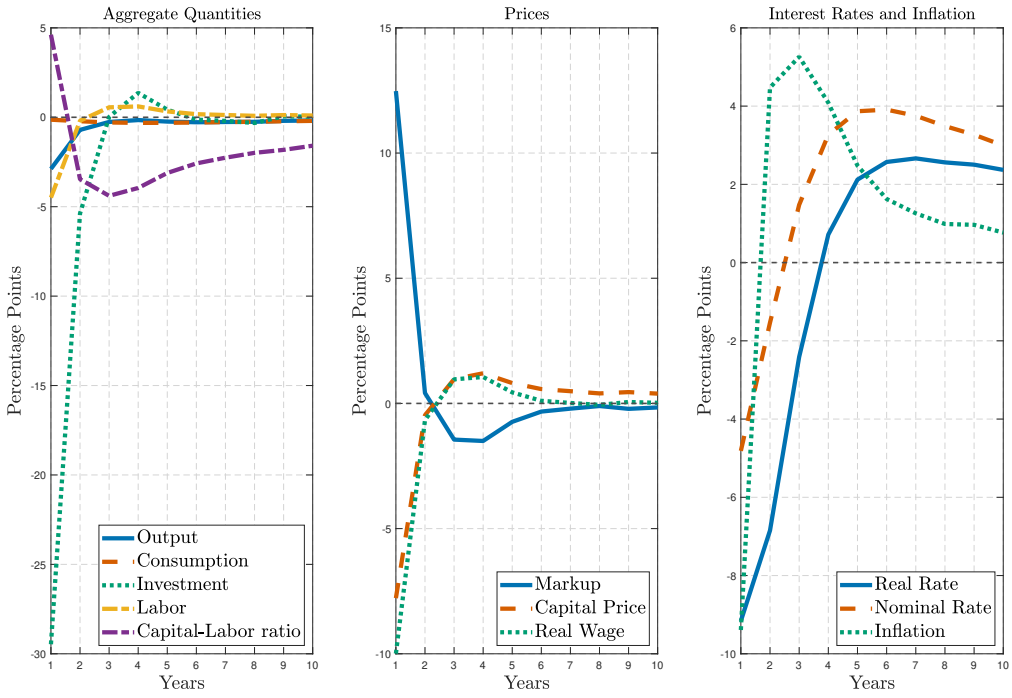
This subsection illustrates two ways financial heterogeneity matters for understanding the aggregate transmission mechanism. We first show that the aggregate effect of a given monetary shock may be weaker when one of the firms has higher leverage in our model. Nevertheless, we show that the aggregate effect of monetary policy is larger in our model than in a comparable version without weaker financial frictions or Cobb-Douglas production function (which collapses to a representative firm).

State-dependence of aggregate transmission To illustrate the scope of state dependence, we compare the baseline response to a monetary shock with a response to monetary policy that hits when firms are more leveraged. Specifically, we do this by computing an impulse response to a joint economy-wide monetary shock and a debt shock to one of the firms hitting at the same time, and subsequently subtracting the response to the debt shock itself.

Figure 2.3 plots the difference between the baseline impulse response to a monetary shock and the state-dependent response. The initial difference is dominated by the demand for investment. If monetary policy expands when firms are very leveraged, they cannot expand investment demand as much as they would have otherwise. Since investment demand is part of aggregate demand, this translates in a smaller response of output and employment, as firms simply do not have to produce as much. In later periods the response is driven more by the capital-labor mix. Since in the leveraged-state one of the firms does not have enough capital, it instead substitutes towards employment. The effect of leverage on the response of output and consumption to monetary policy, at least beyond the first period, is negligible. Figure 2.3 also shows that leverage interferes with monetary policy transmission to prices and inflation, initially muting the response of inflation, wage, and real price of capital while amplifying the effect on the markup.

The results shown in figure 2.3 differ from the heterogeneous effects of monetary policy across firms, highlighting the need to account for general equilibrium effects when evaluating the role of leverage. While the cross-sectional analysis indicated that leverage amplifies the labor demand response in our model, this does not necessarily extend to the aggregate

Figure 2.3: Differential of aggregate impulse responses



Notes: Aggregate generalized impulse responses to a $\varepsilon^m = -10^{-6}$innovation to the Taylor rule which decays at rate $\rho_\varepsilon = 0.4$, and $\varepsilon^v = 10^{-2}$ and $\rho_v = 0.0$. y-axis values are scaled by the standard deviation of σ_{ε^m}

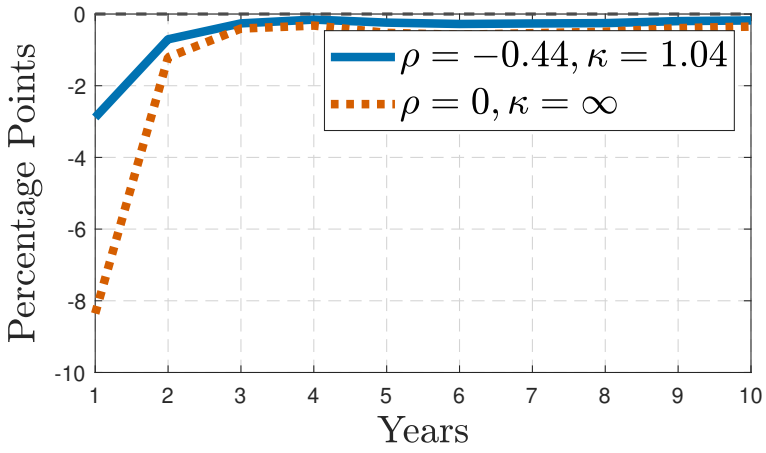
response. Instead, at least in the initial period of the shock, the opposite happens.

Alternative calibration choices To gain additional insight into the mechanisms behind aggregate responses, we compare the effect of monetary policy in our model to alternative calibrations[5].

First, we compare our model with one in which wholesale intermediate goods firms have a production function close to Cobb-Douglas their products are perfectly substitutable.

In Figure 2.4 we plot the same exercise as in paragraph 2.3.3, comparing the difference in output responses. We see that while the responses are similar in shape, the effect of leverage is stronger in magnitude in the standard model.

Figure 2.4: Differential of aggregate output's impulse responses



Notes: Aggregate generalized impulse responses to a $\varepsilon^m = -10^{-6}$innovation to the Taylor rule which decays at rate $\rho_\varepsilon = 0.4$, and $\varepsilon^v = 10^{-2}$ and $\rho_v = 0.0$. y-axis values are scaled by the standard deviation of σ_{ε^m}

Figure 2.5 (a) shows that the effect of monetary policy on output is more persistent but smaller on impact in our baseline calibration than in the alternative. Second, we compare our model to one in which we somewhat relax the dividend constraint. We do so by lowering the threshold bellow which the firm cannot lower its dividend payments[6]. In line with previous studies, the effect of monetary policy is amplified in the model with the stronger constraints (see Figure 2.5 (b) in Appendix B.2). Here the financial accelerator channel

[5]It is worth pointing out that our model collapses to a representative firm model with dividend and collateral constraints whenever only aggregate shocks are allowed.

[6]When lower dividends are not penalized, the firm does not have to raise excessive debt to finance an investment boom.

is operating: when constraints are tight, monetary policy has the additional expansionary effect of loosening them (through higher capital and output prices).

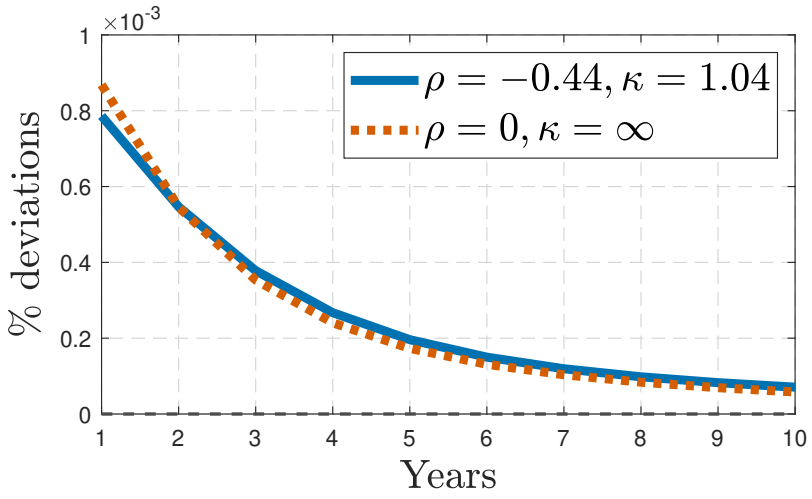
2.4 Conclusion

Our New Keynesian model with financial frictions and flexible CES production reveals that leverage moderates the capital stock response but amplifies it more in standard models than in ours. This suggests that in a standard model with Cobb-Douglas production, financial frictions play a greater role in interfering with monetary transmission. By contrast, the flexibility in our model reduces leverage's aggregate impact.

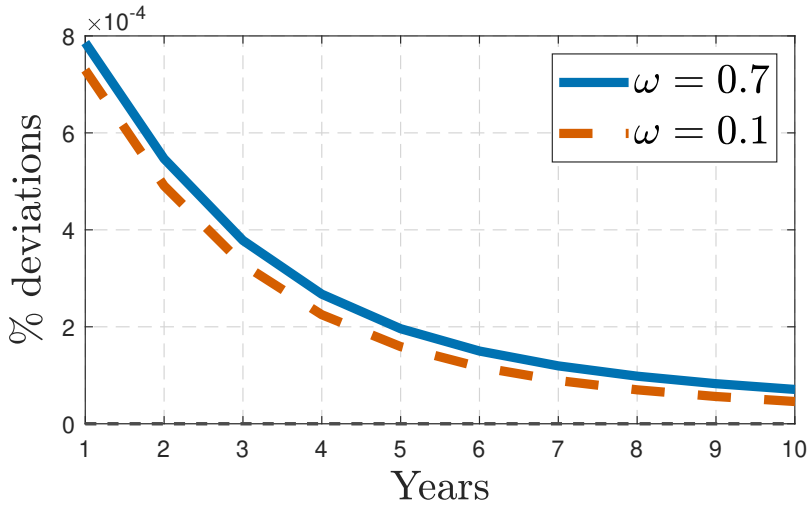
For policymakers, these findings raise concerns about the concentration of labor in highly leveraged firms, potentially heightening economic vulnerability to financial shocks. Macroprudential measures may be needed to complement monetary policy to address this risk and promote balanced employment growth.

Further research is necessary to estimate how these cross-firm dynamics translate into macroeconomic outcomes and ensure that policy designs consider the growing role of financial frictions in a highly leveraged environment.

Figure 2.5: Aggregate output's impulse response



(a) Capital-labor complementarity



(b) Relaxation of dividend constraint

Notes: Aggregate impulse responses to a $\varepsilon^m = -10^{-6}$ innovation to the Taylor rule which decays at rate $\rho_\varepsilon = 0.4$.

CHAPTER 3

Financial Innovation and Firm Growth: Evidence from New Securities in U.S. Capital Markets

3.1 Introduction

Financial innovation plays a critical yet underexplored role in modern capital markets. Firms frequently issue new financial products—variations of debt and equity securities that combine novel contractual terms, legal structures, and payment mechanisms. These innovations are driven by evolving corporate needs to manage financing costs, navigate regulatory constraints, meet investor preferences, and pursue broader strategic goals. Despite the importance and complexity of financial product design, there remains limited understanding of the underlying structure of financial innovation, the types of firms most engaged in such activities, and the conditions under which new instruments emerge and gain traction in the market.

This paper addresses these gaps by studying the dynamics of financial innovation in U.S. capital markets, focusing specifically on the introduction of new debt and equity instruments by non-financial firms. Using detailed transaction-level data from the SDC Platinum Global New Issues database, we construct a high-dimensional classification of financial products based on their contractual features—including maturity structure, callability, convertibility, payment form, and legal attributes. Applying this framework, we identify over 8,500 distinct product types issued between 1970 and 2020, documenting their variation in complexity, adoption scope, and regulatory treatment. This classification provides a new empirical foundation for analyzing where financial innovation occurs and which firms are most likely to introduce novel products.

The analysis proceeds in three parts. First, we define what constitutes a financial innovation in our setting and characterize its main features. We consider a financial instrument

to be "new" for 365 days following its first recorded issuance, allowing us to focus on the early adoption phase when uncertainty about a product's broader viability remains highest. This framework enables direct comparisons between newly introduced and established instruments. We find that new products are typically associated with larger issuance sizes and are more likely to be adopted by firms in specialized sectors or those targeting niche investor segments, suggesting that financial innovation often serves particular financing needs.

Second, we examine broader patterns in the adoption and diffusion of new products across time, sectors, and issuer types. Most new instruments remain narrow in scope, issued by a small number of firms within specific industries, while only a minority gain widespread traction. Patterns of innovation are episodic, with bursts of new product introductions coinciding with major regulatory and macroeconomic shifts, particularly during the mid-1980s and early 2000s. Adoption tends to be more prevalent among subsidiaries of public companies and is often facilitated through flexible regulatory mechanisms such as shelf registration and Rule 144A placements.

Third, we study the firm-level characteristics associated with the introduction of novel instruments by linking transaction-level issuance data to firm fundamentals from Compustat. Several patterns emerge. Firms that issue new financial products are, on average, larger and older than those that rely solely on established instruments. This suggests that the fixed costs and risks associated with failed innovation—such as regulatory hurdles, weak investor demand, or reputational harm—may limit participation by smaller and younger firms. The ability to innovate in financial products thus appears to be conditioned on firm scale and maturity.

Furthermore, we find that early adopters of novel instruments exhibit higher subsequent growth in sales, capital expenditures, and employment relative to firms that issue only traditional securities. Although our analysis is descriptive and does not imply causality, these associations suggest that financial innovation may play an important role in facilitating firm expansion. Access to customized or flexible financing options may help firms pursue strategic investments or operational growth that would otherwise be constrained under standard financing structures.

Taken together, these findings provide motivation for the theoretical framework we develop in future work. In particular, they support modeling financial innovation as an endogenous firm decision, shaped by characteristics such as size, age, and growth potential, and constrained by the costs and uncertainties inherent in introducing new securities.

This paper contributes to three distinct strands of literature. First, it extends the grow-

ing body of research on financial product innovation and the evolution of security design. Several studies have proposed methods to quantify financial innovation. For example, Tufano (2003), Lerner (2006), Schroth (2006), and Herrera and Schroth (2011) identify novel financial instruments by analyzing news coverage in the Wall Street Journal. Babus et al. (2023b) uses the names of securities as identifiers for new types, while Lerner et al. (2021) relies on patent data to classify innovations. In contrast, this study adopts an approach commonly used in the consumer product innovation literature (e.g., Argente et al. (2020); Kogan et al. (2017)), which defines financial products in terms of their specific contractual features and identifies innovation based on the introduction of new products in the market.

Second, the paper contributes to the literature on firm financing decisions, which emphasizes that these decisions are influenced by firm-specific characteristics rather than being uniform or arbitrary (Graham and Leary (2011); Frésard and Phillips (2024)). While much prior research has focused on broad choices between debt and equity, more recent studies—such as Colla et al. (2013) and Rauh and Sufi (2010)—examine how factors like firm size, leverage, and growth opportunities affect the structure of debt financing. This paper extends that work by demonstrating that these same firm characteristics also predict the likelihood of adopting newly introduced financial instruments. Specifically, it finds that larger firms, as measured by total assets, sales, or employment, and those with higher leverage, are more likely to utilize innovative financial products.

Third, the literature on financial innovation has primarily focused on the impact of such innovations on investors, with less attention paid to their effects on issuing firms. Theoretical models (e.g., Thakor (2012); Gennaioli et al. (2012); Caballero and Simsek (2013); Biais et al. (2015)) suggest that complex securities can shift risks and create informational asymmetries that disadvantage investors. Empirical studies on specific financial instruments—such as SPARQS (Henderson and Pearson (2011)), structured notes (Bergstresser (2008)), and auction rate securities (Han and Dan (2010))—have documented negative outcomes for investors. Even studies with a more optimistic view, such as Calvet et al. (2023), continue to focus primarily on investor experience rather than firm-level effects.

In contrast, this paper focuses on the impact of financial product innovation on firms. The analysis demonstrates that firms that adopt novel financial instruments tend to exhibit higher subsequent growth in sales, capital expenditures, and employment compared to firms relying solely on traditional instruments. Notably, this paper finds no significant association between the adoption of innovative securities and increased R&D expenditures, which contrasts with Babus et al. (2023a), who reports a positive relationship between financial innovation and

firm innovativeness. This divergence is partly due to methodological differences: Babus et al. (2023a) identifies financial innovation based on the names of securities, whereas this paper defines financial products through a comprehensive set of contractual features.

3.2 Data

We gather comprehensive data to conduct an in-depth study of corporate security issuances. A security issuance represents a new agreement between a firm (the issuer) and investors, enabling the firm to raise capital while granting investors a claim on future cash flows. For the purposes of this analysis, we refer to this agreement as a "financial product."

Our primary data source is the Global New Issues modules from the Security Database Company Platinum Dataset, published by LSEG Data (referred to hereafter as SDC Platinum). This database includes all public, private, and Rule 144A issuances of corporate securities with maturities longer than one year (where applicable), excluding derivatives, from 1970 onwards. We focus specifically on transactions targeting the US capital market. For each security issuance, we record the date, the name of the issuing firm, and key deal characteristics. SDC reports the currency of issuance, coupon type, rate, payment frequency, seniority, as well as call and put provisions, among other characteristics. Importantly, we also capture the amount of capital raised in each issuance—referred to as the proceeds.

The data encompasses issuances from non-financial corporations, the US government, federal agencies, and financial institutions. Our sample spans the period from 1970 to 2020, allowing us to define the year a product is introduced as the year it first appears in the dataset. The data cleaning procedure, based on the guidance of Boyarchenko and Elias (2024), is described in the Appendix C.1.

The baseline dataset includes 530,555 issuances by 66,296 issuers, covering both publicly listed and private entities across 961 four-digit SIC sectors. There is substantial variation in issuance activity across sectors over the sample period. Issuers in the FIRE sector[1] are the most prolific, with an average of 40,286 issues per issuer and a median of 51,482. They are followed by public sector issuers[2], which average 100 issues per issuer, with a median of 25. In contrast, real economy issuers[3] are far less active in capital markets, with an average of 22 issues per issuer and a median of just 7.

[1]The FIRE sector includes finance, insurance, and real estate, corresponding to 2-digit SIC codes 60–67

[2]2-digit SIC codes 91–97

[3]Defined as issuers outside the FIRE sector, public administration, and utilities; excludes 2-digit SIC code 49

We identify each product as a unique combination of issuance characteristics reported in SDC Platinum[4], including maturity type, coupon type, coupon structure, currency of denomination, call and put provisions, and conversion mechanisms, among others. This approach complements alternatives that rely on the instrument type field in SDC Platinum (e.g., Babus et al. (2023b)), which can group together securities that differ in economically relevant features, such as embedded call options or voting rights in equity instruments. Similarly, while media coverage has been used to track financial innovation (e.g., Lerner (2006)), such coverage may not capture all newly introduced products, particularly those with more incremental features or narrower investor appeal. Full details on the specific variables used and the construction procedure are provided in Appendix C.2.

As reported in Table (3.1), we identify 8,513 distinct types of financial products—compared to 751 identified for non-financial firms by Babus et al. (2023b)—with an average total issuance of USD 10,531 million per product. These products tend to be highly specialized: the median product is issued by only 3 issuers across 2 sectors. However, on average, a product is issued by 14.6 issuers and appears in nearly 5 sectors over the sample period. Around 10 percent of the transactions were issued via the private market[5], 18 percent of

Table 3.1: Descriptive statistics

	Obs	Mean	St.Dev.	P25	P50	P75	P90
Transaction							
Proceeds, in millions US$ (real)	524,648	170.89	344.15	14.08	53.91	207.04	442.64
Filling: Private	530,555	0.10	0.30	0.00	0.00	0.00	0.00
Filling: Shelf reg.	530,555	0.18	0.38	0.00	0.00	0.00	1.00
Filling: Rule 144A	530,555	0.07	0.25	0.00	0.00	0.00	0.00
Product							
Proceeds, in millions US$ (real)	8,513	10,531.93	159,798.32	85.44	308.98	1,292.63	5,772.72
Issuances	8,513	62.32	1,079.06	1.00	2.00	6.00	22.00
Issuers	8,513	14.58	213.05	1.00	1.00	3.00	10.00
Sectors	8,513	4.84	26.32	1.00	1.00	2.00	6.00
Product × Sector							
Proceeds, in millions US$ (real)	38,470	2,319.52	61,851.66	45.57	158.35	527.04	1,816.57
Issuances	38,470	13.71	249.91	1.00	1.00	3.00	10.00
Issuers	38,470	3.96	19.53	1.00	1.00	2.00	6.00

Notes: The table provides various descriptive statistics of the SDC Platinum dataset at transaction level, financial product level and product × sector level. Various levels of fillings are dummy variables, which take value of 0 and 1, while issuances, issuers and sectors (defined by 4-digit SIC codes) refer to simple quantities.

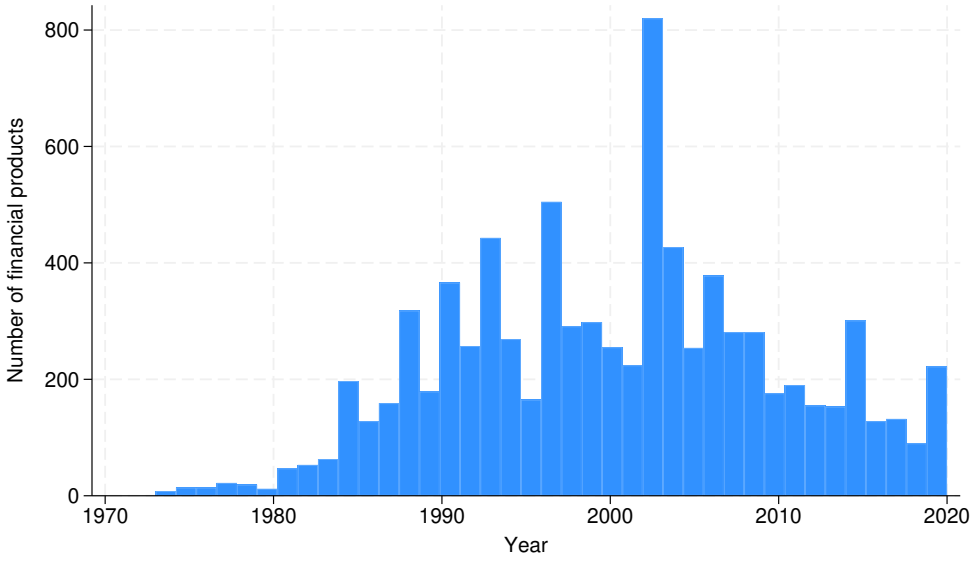
[4]SDC derives contractual characteristics from various sources, including SEC filings, prospectuses, industry news outlets, wire services, and daily surveys of underwriters and corporate finance professionals.

[5]Private markets for securities refer to capital markets where financial instruments—such as equity, debt,

transactions are shelf-registration [6], and 7 percent were issued via Rule 144A[7]

Figure (3.1) shows the annual evolution of new financial product introductions over the sample period. The number of new products began to rise significantly in the mid-1980s, with steady growth leading to a peak in 2003, when a record 800 new products entered the market. This surge can be linked to the introduction of the shelf registration rule in 1982, which gave issuers greater flexibility in the timing of their security offerings. After 2003, the trend reverses, with a general decline in new product introductions, though notable spikes occur, particularly in 2014, following the implementation of Rule 144A, which eased registration requirements for securities sold to qualified institutional buyers (QIBs).

Figure 3.1: Total number of products introduced in a year



Notes: This figure displays the number of financial instruments introduced to the market for the first time each year from 1973 to 2020. The horizontal axis represents the year of introduction, while the vertical axis indicates the count of newly launched instruments per year. We exclude the years 1970–1972, treating them as baseline years under the assumption that no new instruments were introduced during that period.

or hybrid securities—are issued and traded without being registered with a public exchange or regulatory body like the SEC. These markets are characterized by limited disclosure requirements, restricted investor access (typically to institutional or accredited investors), and the absence of centralized trading venues.

[6]Shelf registration is a regulatory provision that allows issuers to register a new issue of securities with the SEC and delay the actual sale for up to three years, enabling them to offer the securities quickly when market conditions are favorable.

[7]Rule 144A is a regulation issued by the U.S. Securities and Exchange Commission (SEC) that allows the resale of certain privately placed securities to qualified institutional buyers (QIBs) without the need for SEC registration, facilitating faster and more efficient access to capital markets for issuers.

Figure (3.2) illustrates the heterogeneity in the adoption of financial instruments across firms and sectors between 1970 and 2020. Panel (a) plots the total number of firms that have issued a given instrument against the number of sectors in which the instrument has been adopted. Panel (b) presents the average within-sector firm adoption rate—defined as the mean share of firms within a sector that have issued the instrument—against the number of sectors. Each point represents a distinct financial instrument, with marker size proportional to the mean principal amount issued per transaction and color denoting the decade of initial introduction.

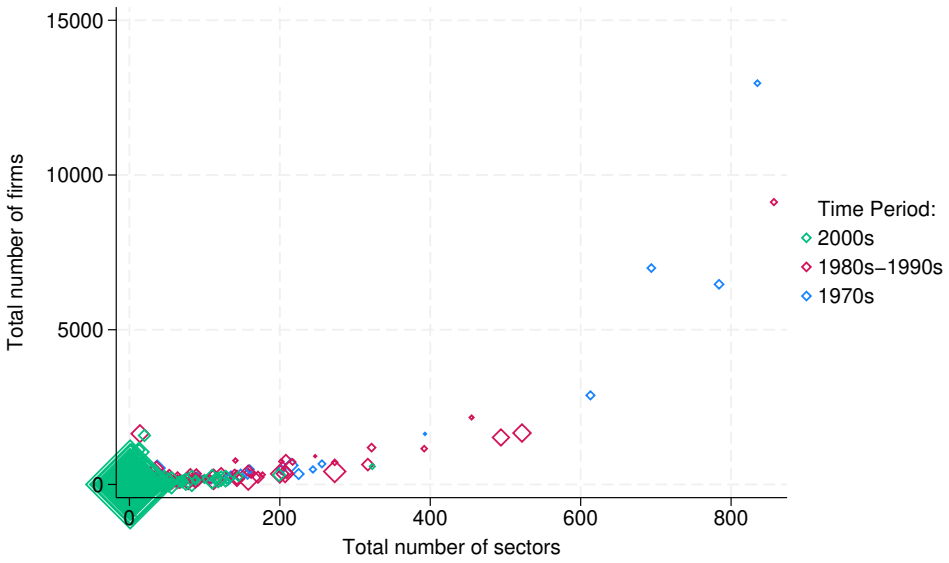
The results reveal that most financial instruments remain highly specialized, adopted by relatively few firms and confined to a limited number of sectors. Nonetheless, several products exhibit widespread diffusion. Notably, the instruments with the broadest adoption—those issued by numerous firms across a wide range of sectors—include several introduced in the early years of the sample, particularly around 1973. For example, one of the most widely used products is a fixed-rate bond with unspecified maturity, non-callable until maturity, first introduced in the private market in the early 1980s. Other highly diffused instruments—such as fixed-rate bonds with "make-whole call" provisions or those callable only after a specified date—were introduced later but still gained significant traction across firms and sectors.

The most widely adopted equity instrument introduced after 1973 is non-voting common stock, first issued in 1981. These patterns suggest that products with complex or exotic features tend to have limited adoption, likely due to their high degree of specialization and lower marketability.

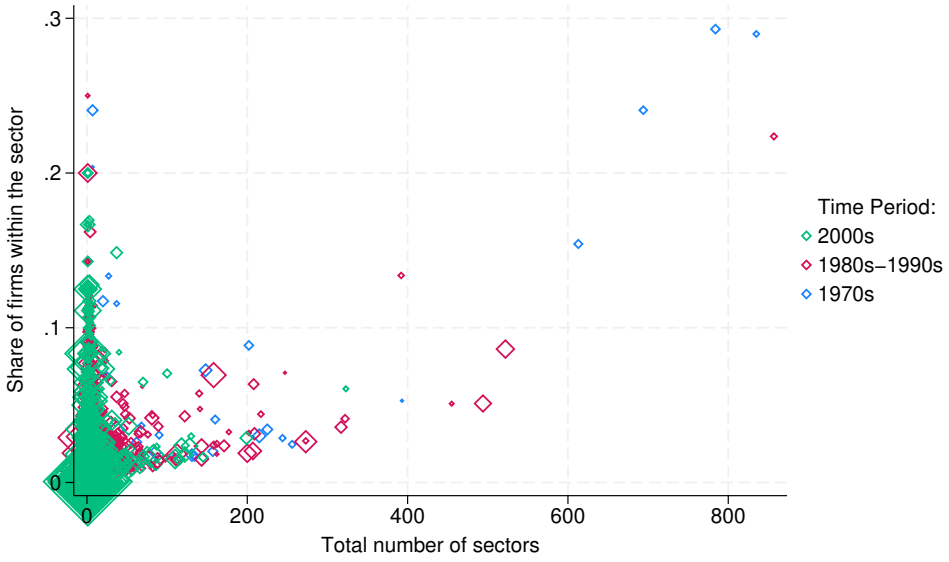
Surprisingly, despite lower diffusion, financial products introduced in the 2000s dominate in terms of average issuance size. The product with the highest average transaction value—US$9.8 billion per issuance—was voting common stock issued by Saudi Arabian Oil Co., denominated in Saudi Riyals and launched on the U.S. private market. Other notable high-value instruments include a fixed-rate bond with a poison put feature, scheduled early redemption, and non-callability until maturity, as well as a credit-sensitive, fixed-coupon bond with bullet maturity and a make-whole call option—each exceeding US$8 billion in average issuance.

Figure 3.2: Allocation of Financial Products Across Sectors and Firms

(a) Relationship between number of issuing firms and sectors.



(b) Relationship between share of issuing firms and sectors.



Notes: Panel (a) visualizes the relationship between the total number of firms and sectors associated with each financial product. Panel (b) shows the relationship between the average share of firms issuing a product across sectors and the number of sectors where the product is issued. Each diamond represents a financial instrument, sized by relative mean principal amount per issuance, and colored by the decade of first introduction. Panel (b) includes only products issued by more than one firm within a sector.

Panel (b) Figure (3.2) also highlights a class of highly specialized instruments adopted by a large share of firms within a single industry. Interestingly, instruments introduced in the 2000s dominate the top of this distribution. The top two instruments by intra-sector firm adoption include: (1) voting common stock denominated in Brazilian Cruzeiro Real, issued in 1996 by firms in SIC 3534 (elevators and moving stairways); and (2) voting ordinary shares issued in Singapore Dollars by firms producing animal and marine oils, featuring a pari passu covenant. The use of non-USD denominations in these cases underscores the tailored nature of these instruments and the distinct currency risk exposures they may offer to investors.

For a more detailed examination, Figure (C.1) in Appendix C.5 presents a finer breakdown of Panel (a) from Figure (3.2) by decade of introduction. Figures (C.2) and (C.3) replicate Panels (a) and (b), respectively, but restrict the sample to instruments falling within the 99th percentile of firms and sectors, allowing for a more detailed exploration of the most widely adopted products.

3.3 New financial instruments

As evidenced in earlier sections, only a small subset of instruments ultimately achieves widespread adoption across firms and sectors. This implies that issuing highly specialized instruments may entail substantial risk for both the issuer and the underwriter, particularly if the product fails to gain traction in the market. In the subsequent analysis, we investigate the types of firms that initiate new financial products and examine whether early adoption is systematically associated with real firm outcomes—specifically, changes in research and development (R&D) activity, capital investment, sales growth, or employment. In addition to firm-level outcomes, we also compare newly introduced instruments to the broader universe of financial products in terms of issuance size, patterns of sectoral adoption, and legal or regulatory environments. This allows us to better understand the distinguishing features of new instruments and the conditions under which they emerge.

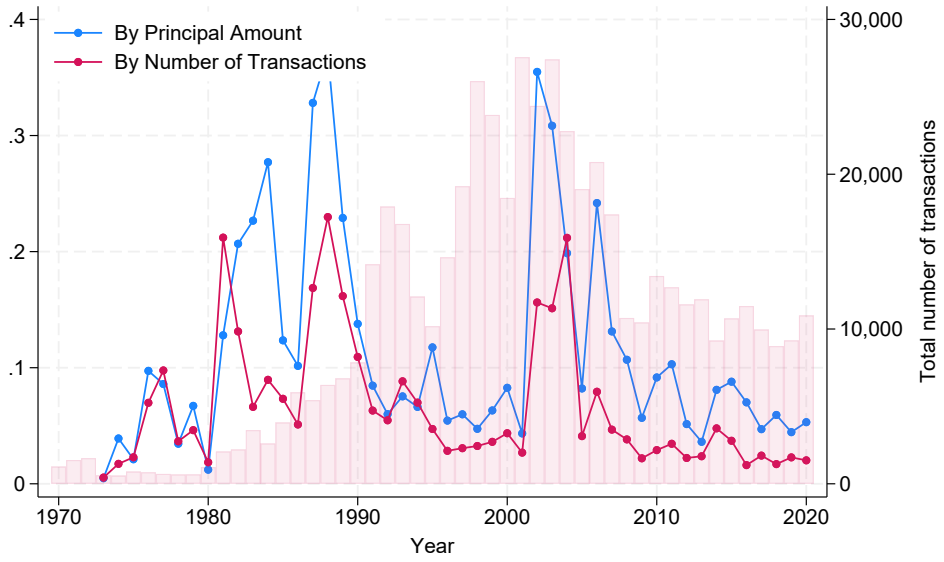
To better understand the dynamics of financial innovation, we next focus on newly introduced financial instruments. An instrument is classified as new for a period of 365 days following its first issuance in the market. This definition allows us to isolate the early adoption phase, during which market participants face heightened uncertainty regarding the product's potential for broader diffusion.

3.3.1 Issuance Patterns and Adoption Contexts

For each year, we identify whether a transaction involves a new financial instrument. Figure (3.8) plots the evolution of new instruments over time, presenting the share of total principal raised and the number of transactions involving new instruments (left axis), alongside the total number of transactions per year (right axis), over the period 1973–2020.

We begin by characterizing the aggregate issuance patterns of new financial instruments over time. Figure (3.8) shows the annual share of total principal and number of transactions involving new products, alongside the total volume of transactions from 1973 to 2020. Overall market activity peaked in the mid-2000s before declining and stabilizing at around 10,000 transactions per year. While new instruments typically account for less than 10 percent of the market by either measure, two distinct waves of innovation stand out: one in the mid-1980s, and another in the early 2000s. These surges coincide with periods of macroeconomic instability—such as high inflation and dollar depreciation in the 1980s, and the post-9/11 and financial crisis environment in the 2000s—suggesting that innovation may be partially driven by external economic shocks.

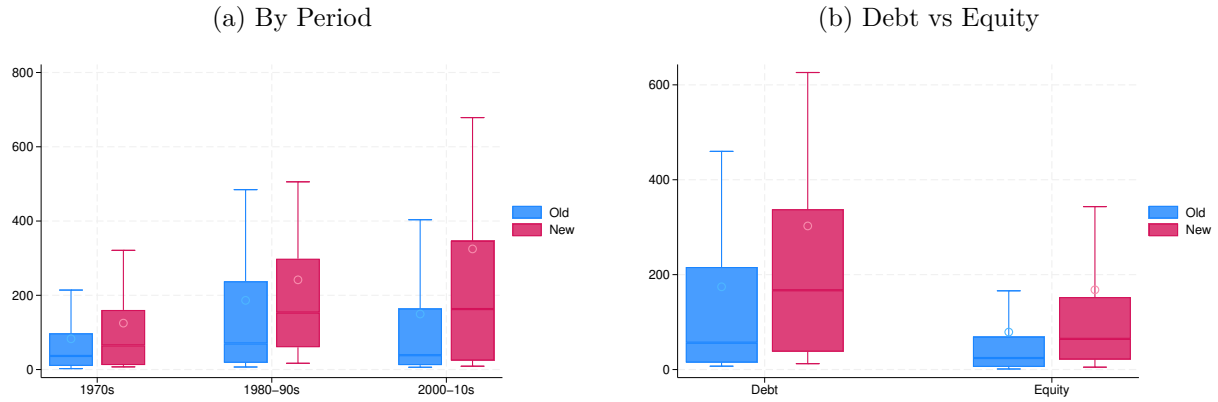
Figure 3.3: Share raised via new instruments



Notes: This graph shows the share of capital raised through new financial instruments introduced each year from 1973 to 2020, categorized by principal amount and number of transactions. The financial instrument is considered new for 365 days after the first transaction.The horizontal axis represents the year of introduction. The right scale indicates the total number of transactions made during the year.

Figure (3.4) documents the evolution of transaction size. Panel (a) shows that the average issuance size for new instruments increased steadily over time, reaching nearly $180 million (in real terms) during the 2000s–2010s. In contrast, the average size of old (non-new) instruments peaked in the 1980s and declined thereafter. Panel (b) confirms that across both debt and equity categories, new products tend to involve larger proceeds than their traditional counterparts.

Figure 3.4: Distribution of proceeds per issuance (in millions of US$, real) by period and type of instrument

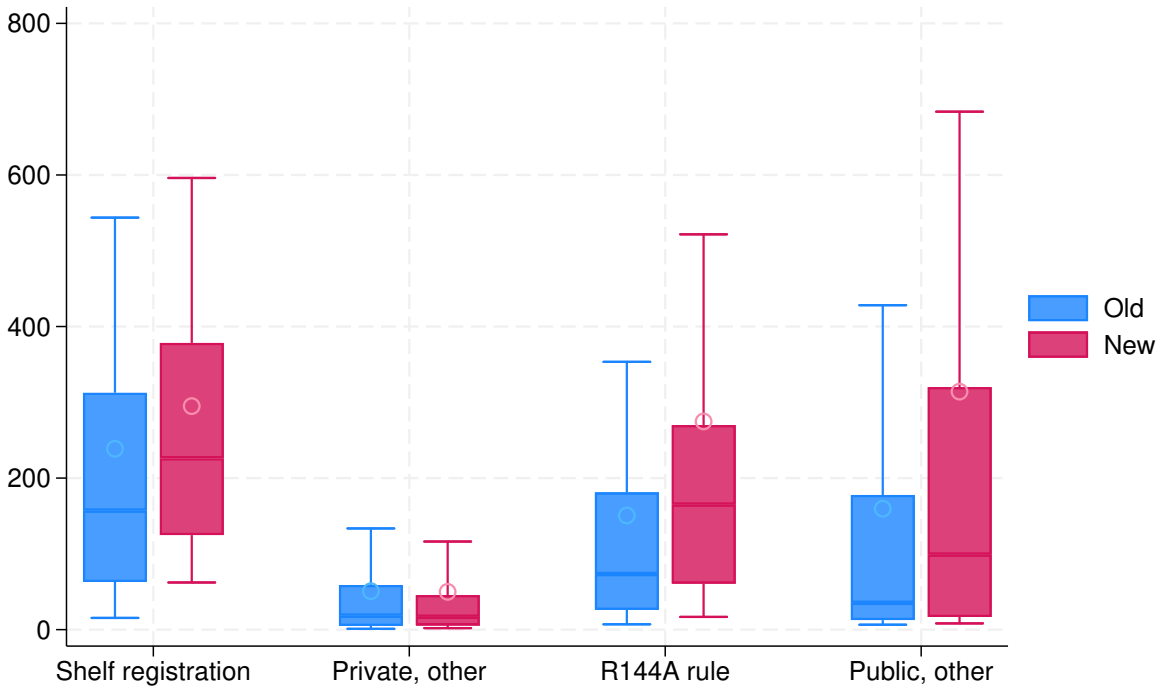


Notes: This Figure shows distribution of proceeds per issuance. Each panel compares transaction-level distributions for new and old instruments. Instruments are considered new within 365 days after their first issuance. Each boxplot shows the 10th percentile, lower quartile, median, upper quartile, and 90th percentile; the dot represents the average.

Appendix C.6 figure C.4 further shows that innovation is not disproportionately skewed toward either debt or equity issuance, but instead mirrors the overall financing mix.

Figure (3.5) shows that more flexible regulatory regimes—such as shelf registration and Rule 144A placements—are associated with significantly larger transaction sizes for new instruments, relative to traditional public and private placements. These channels appear to facilitate the marketing and distribution of innovative products under conditions of uncertainty.

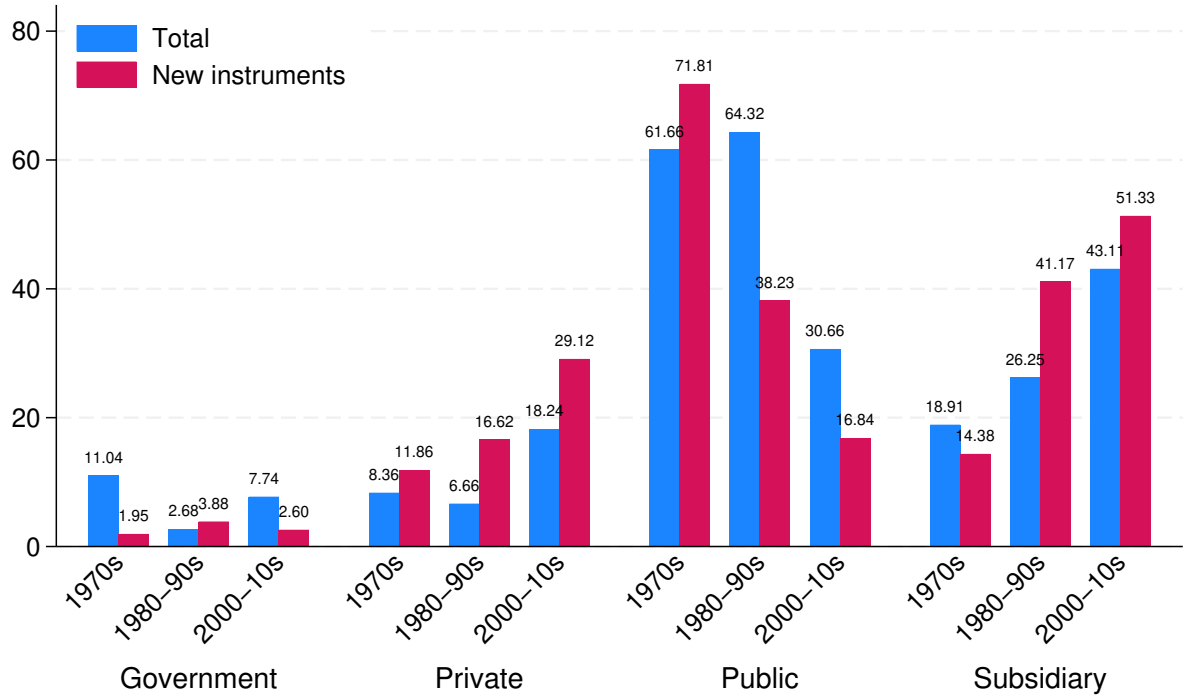
Figure 3.5: Distribution of proceeds per issuance (in millions of US$, real) by issuance rule



Notes: The figure presents the distribution of proceeds per issuance (in millions of US$, real) at the transaction level, with statistics for the placement rule included. A financial instrument is considered new for 365 days after its first transaction. For each instrument type, we display five sample statistics: the 10th percentile, lower quartile, median, upper quartile, and 90th percentile. The dot represents the average proceed for each instrument type.

Turning to issuer types, Figure (3.6) shows that the share of novel issuance by subsidiaries of companies has grown substantially over time. By the 2000s–2010s, subsidiaries accounted for more than half of all new-issue principal, while private firms contributed about 30 percent. This is in contrast to their respective shares in total issuance (43 percent and 19 percent), suggesting that public companies may be using subsidiaries to ring-fence potential risks associated with novel products.

Figure 3.6: Incidence by the type of issuer



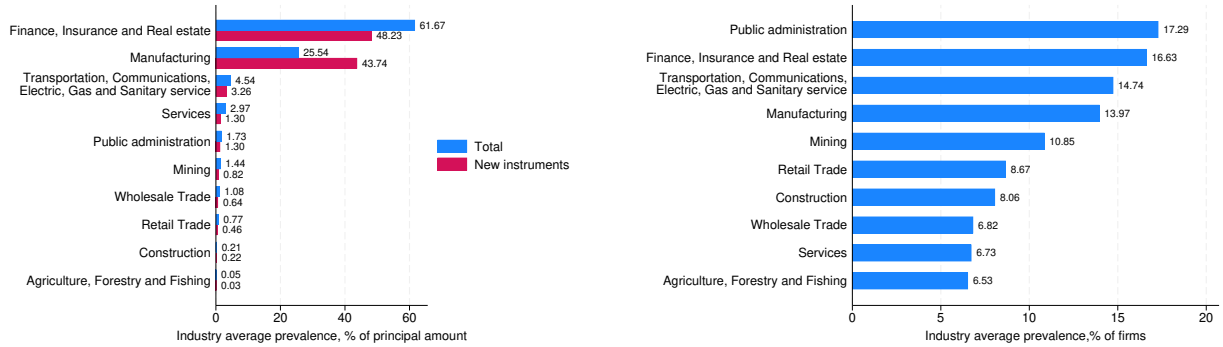
Notes: This graph shows the percentage of the principal amount in both the total market and the market for newly issued instruments, categorized by issuer public status, over sample subperiods from 1970 to 2020. A financial instrument is considered new for 365 days after its first transaction. The horizontal axis represents the year of introduction.

Figure (3.7), Panel (a), provides a sectoral breakdown, highlighting the relative incidence of new instruments by principal amount. FIRE (Finance, Insurance, and Real Estate) firms dominate total issuance but are underrepresented in the use of new instruments. In contrast, manufacturing firms—although representing a smaller share of total issuance—are overrepresented in novel product adoption. This contrast suggests that innovation is not uniformly adopted and may reflect differences in risk tolerance, regulatory constraints, or funding needs.

Figure 3.7: Incidence of New Instruments: Market and Industry Perspectives

(a) Share of principal issued by industry.

(b) Share of firms issuing new instruments.



Notes: Panel (a) shows the percentage of the principal amount in the total market and the market of new instruments issued by each industry over the sample period 1973–2020. Panel (b) reports the percentage of firms which issued a new instrument at least once over the sample period 1970–2020. For both panels, the financial instrument is considered new for 365 days after the first transaction.

Panel (b) of the same figure shows that within each industry, only a small fraction of firms experiment with new instruments. This selective adoption is consistent with the idea that introducing a novel security entails uncertainty and reputational risk. Interestingly, firms in the Public Administration sector lead in within-sector adoption, with 17 percent having issued at least one new product. This finding aligns with evidence from Brancaccio and Kang (2022), who document increasing complexity in municipal bond markets and an associated rise in funds raised by local governments through structured instruments.

These descriptive patterns provide a foundation for our next step: linking issuance data to firm-level characteristics using Compustat. This allows us to examine whether early adoption of new financial instruments is systematically associated with differences in firm fundamentals and real economic outcomes.

3.4 Compustat

3.4.1 Matching and Summary Statistics

The firm-level data are sourced from Compustat and contain information on firms' balance sheets. We match the cleaned SDC Platinum transaction data to Compustat firms using issue CUSIP, issuer CUSIP, and the issuer's parent company CUSIP (see Appendix C.3 for

details).Firms are defined by Compustat identifiers (gvkey).

Table (3.2) reports the summary statistics.

Table 3.2: Summary Statistics of Compustat Firms by Issuance Activity and Security Type

			Firm Characteristics (Averages)							
	Obs.	# Firms	Age	Employment	Total assets	Capital	Sales	Leverage	Positive R&D, share	R&D
All	428,213	34,079	14	6.10	1,914.38	630.45	752.75	0.88	0.29	27.54
Financial										
Non-Matched	104,271	10,462	11	2.03	3,571.34	149.68	424.65	1.14	0.02	1.47
Only Old	9,575	3,277	16	5.77	11,036.27	247.00	1,189.34	0.34	0.02	0.77
Some New	1,623	681	28	21.77	77,578.47	744.30	6,067.04	0.39	0.01	0.77
Utilities										
Non-Matched	14,272	773	30	2.82	2,342.67	1,876.64	847.32	0.75	0.03	0.65
Only Old	4,129	455	45	5.32	3,906.70	2,964.16	1,481.15	0.42	0.02	2.74
Some New	383	155	51	9.44	7,982.04	5,428.947	3,109.66	0.42	0.02	10.77
Non-Financial										
Non-Matched	259,502	22,786	14	5.69	641.27	268.50	601.15	0.93	0.40	24.82
Only Old	32,637	12,081	16	13.19	1,831.89	829.98	1,597.38	0.46	0.49	49.30
Some New	1,821	1,171	27	44.56	10,804.74	3,117.67	6,721.20	0.38	0.43	335.26

Notes: Statistics are based on firm-year observations from Compustat over the period 1970–2016. Non-matched firms refer to those that were not linked to any security issuance in the SDC data during the sample period. Within each sector group, the last two rows distinguish matched issuer-firms based on the types of securities issued: those that issued only traditional (non-novel) securities, and those that issued at least one novel security type at any point during the sample period. All variables, except leverage, are expressed in millions of real USD (deflated to January 2000 using the CPIAUCNS index). Detailed definitions of all variables used in the analysis are provided in Appendix C.4

Approximately 52% of publicly listed firms in our Compustat sample are matched to at least one security issuance at SDC Platinum database over the sample period of 1970-2016, with only 11% of these matched firms issuing novel security types. Firms that adopt new securities are, on average, significantly larger in terms of employment, assets, sales, tangible capital, and R&D expenditures (in the case of non-financial and utility firms) compared to firms that issue only traditional securities or those not matched to any issuance. These patterns are consistent with the findings of Lerner (2006), Lemmon et al. (2014), and Babus et al. (2023b). Firms that issue innovative instruments do not differ meaningfully in leverage. Interestingly, non-financial firms that adopt novel instruments are slightly less likely to report positive R&D expenditures. Across all sectors, firms active in capital markets and issuing novel instruments also tend to be older, aligning with prior evidence in Lerner (2006).

Table (3.3) reports the size of funds raised within a given year relative to total assets

measured at the end of the previous year. This metric captures the scale of issuance activity in proportion to firm size. The results show that total issuance using only traditional instruments is exceptionally large compared to lagged assets, particularly among non-financial and financial firms. On average, non-financial firms raise funds equal to 41 times their prior-year assets, while financial firms raise around 35 times. The composition of issuance differs notably: financial firms predominantly raise equity—32 times their lagged assets—while debt issuance is more limited, at 3.45 times. In contrast, non-financial firms rely heavily on debt, issuing 37 times their lagged assets in debt and only 5 times in equity. Utility firms are significantly more moderate, raising funds equivalent to just 0.2 times their prior-year assets.

Firms are considerably more conservative in years when novel instruments are used. Among non-financial firms, total issuance in such years amounts to 0.83 times lagged assets, with novel debt accounting for 0.40 times and novel equity for 0.18 times. Financial firms are even more restrained, issuing just 0.15 times their lagged assets through novel debt and 0.06 times through novel equity. These patterns run counter to the expectation that financial firms are the primary adopters and beneficiaries of financial innovation; instead, they appear to be more cautious than non-financial firms in employing novel security designs.

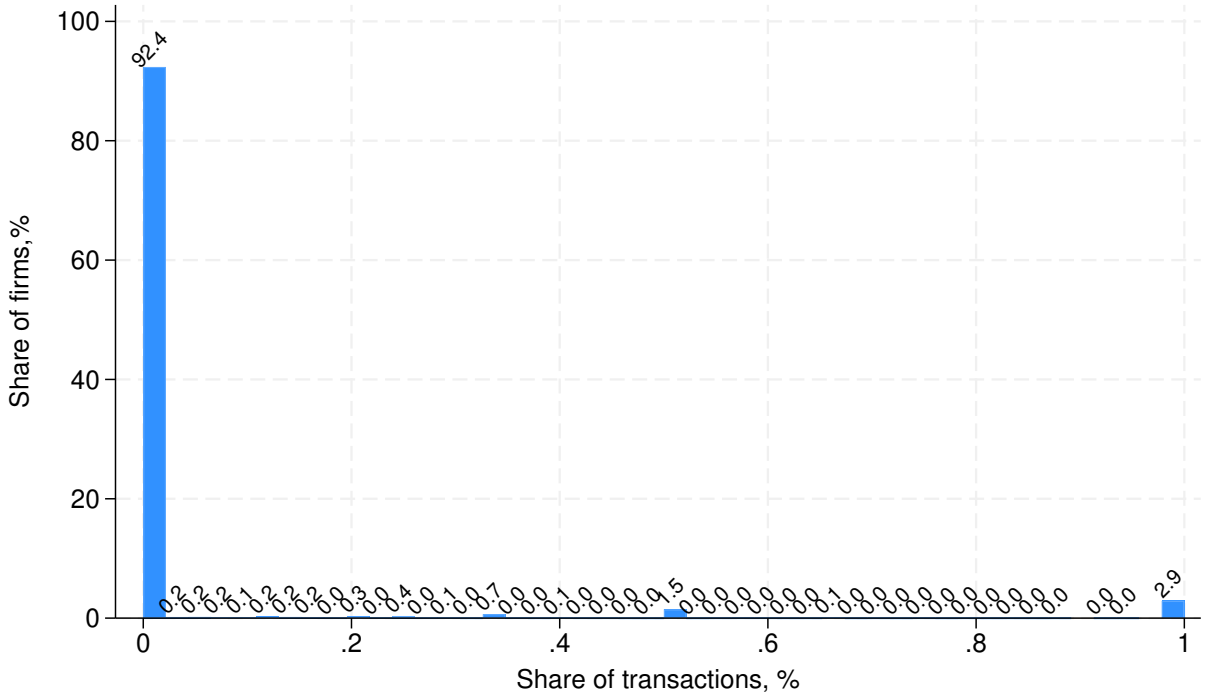
Table 3.3: Relative Size of Funds Raised to Lagged Total Assets by Firm Type and Instrument Type

	All	New only	All, Debt	New only, Debt	All, Equity	New only, Equity
Financial						
Only Old	35.78		3.45		32.33	
Some New	0.65	0.17	0.59	0.14	0.06	0.00
Utilities						
Only Old	0.18		0.08		0.10	
Some New	0.18	0.08	0.14	0.06	0.04	0.00
Non-financial						
Only Old	41.75		36.86		4.89	
Some New	0.83	0.51	0.65	0.40	0.18	0.01

Notes: This table reports the average size of funds raised within a given year relative to total assets measured at the end of the previous year, across firm types (non-financial, financial, utilities) and by instrument type (traditional vs. novel; debt vs. equity). The sample includes only firm-year observations in which firms raised funds via debt or equity instruments during the period 1973–2016.

Figure (3.8) illustrates the distribution of novel instrument usage among firms that raised funds through debt or equity. For each firm-year, we calculate the share of transactions involving novel instruments and plot the distribution of these shares across the sample. A notable pattern is the rarity of novel instrument issuance: in over 90% of firm-year observations, firms raised funds exclusively through traditional instruments. Conversely, only about 3% of firms recorded years in which all of their issuances involved novel designs. Figure (C.6) presents analogous results based on the share of total principal issued using novel instruments.

Figure 3.8: Distribution of Novel Instrument Usage Across Firm-Year Observations



Notes: This histogram displays the distribution of firm-year observations by the share of transactions involving novel financial instruments among firms that issued either debt or equity over the sample period of 1973-2016. The x-axis represents the proportion of a firm's transactions in a given year that involved novel instruments, ranging from 0 (no novel instruments used) to 1 (only novel instruments used). The y-axis indicates the frequency of firm-year observations corresponding to each share interval.

For the remainder of the analysis, we restrict our sample to firm-year observations in which non-financial firms raised external funds through either debt or equity instruments. This focus ensures that we analyze only those firms that were active in capital markets and for which instrument-level matching was successful.

3.4.2 New instruments and firm size

To document the systematic relationship between issuers and firm size, we estimate variations of the following regression:

$$\mathbf{1}\{\text{New Instrument} > 0\}_{j,t} = \alpha_j + \alpha_{s,t} + \beta \log \text{size}_{j,t-1} + \Gamma_t' Z_{j,t-1} + \epsilon_{j,t}, \tag{3.4.1}$$

where $\mathbf{1}\{\text{New Instrument} > 0\}_{j,t}$ is a binary indicator variable that equals 1 if firm j raises funds using at least one novel instrument in year t, and 0 otherwise, indicating that the firm raises funds exclusively through non-novel instruments; $\text{size}_{j,t-1}$ represents a measure of firm size, defined as either real total assets, real sales, or employment; $Z_{j,t-1}$ is a vector of firm-level control variables, including standardized measures commonly used in corporate finance literature such as firm age, leverage, real sales growth, and the ratio of current to total assets; α_j denotes firm j's fixed effect; and $\alpha_{s,t}$ represents a sector s by year t fixed effect. We compute two-way clustered standard errors by firm and year. Detailed definitions of all variables used in the empirical analysis are provided in Appendix C.4.

Table (3.4) presents the estimation results from equation (3.4.1), highlighting a consistent and robust link between firm size and the likelihood of issuing novel financial instruments. Across all specifications, a one-standard-deviation increase in firm size is associated with an approximate 0.02 percentage point rise in the probability of utilizing such instruments—equivalent to 40% of the sample mean probability. This effect is statistically significant at the 99% level when size is measured by real sales or real assets, and at the 90% level when using employment as the size proxy.

Among the control variables included in equation (3.4.1), firm age, sales growth, and ratio of current to total assets do not exhibit statistically significant effects. However, leverage shows a positive and marginally significant relationship with the probability of novel issuance at the 90% level in the specification where firm size is captured by real total assets.

The regressions in Table (3.4) yield R^2 values around 0.38, indicating that a substantial portion of the variation in the probability of issuing novel instruments is explained by firm characteristics—particularly firm size. This highlights the predictive power of these variables and motivates their inclusion as controls in the subsequent outcome analysis, where we aim to isolate the association between novel financing on firm performance.

Table 3.4: Engagement with new financial instruments and firm characteristics

	Probability to issue some novel instrument					
	(1)	(2)	(3)	(4)	(5)	(6)
Log real assets	0.027***	0.031***				
	(0.006)	(0.010)				
Log real sales			0.019***	0.020**		
			(0.005)	(0.008)		
Log employment					0.016*	0.019
					(0.008)	(0.012)
Log age		-0.007		-0.006		-0.007
		(0.008)		(0.008)		(0.008)
Leverage		0.091*		0.069		0.055
		(0.053)		(0.044)		(0.047)
Real sales growth		0.001		-0.000		0.001
		(0.001)		(0.001)		(0.001)
N	21867	17315	20799	17315	19078	16301
R^2	0.373	0.376	0.375	0.376	0.375	0.380
Time sector FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Double clustering	yes	yes	yes	yes	yes	yes

This table reports results from estimating variants of equation (3.4.1). All firm variables are standardized across the sample. Standard errors are clustered by firm and quarter. Standard errors in parentheses. Significance levels:$*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

3.4.3 New instruments and firm behavior

Next, we study the relationship between the use of novel financial instruments and the decisions of companies about investment and growth.

We address this by estimating local projections à la Jordà (2005), allowing us to capture the dynamic effect on firms' oucomes following financing raised through innovative instruments. Specifically, we regress the cumulative change in a variable of interest $\Delta_h \log y_{j,t+h} (\equiv \log y_{j,t+h} - \log y_{j,t-1})$ for the firm j over a given horizon $-4 \leq h \leq 5$ on a dummy variable that captures the use of new products at time t, while controlling for various characteristics at the firm level.

We estimate our baseline empirical specification on a subsample of matched non-financial firms.

$$\Delta \log\, y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h \mathbf{1}\{\text{New Instrument} > 0\}_{j,t} + \Gamma_h' Z_{j,t-1} + \epsilon_{j,h,t+h}, \qquad (3.4.2)$$

where $y_{j,t+h}$ is firms' employment, capita, sales or the cumulative probability of positive R&D expenses. $\alpha_{j,h}$ denotes firm j's fixed effect in it's cumulative $h+1-$ year y_j $-$ growth. $\alpha_{s,t,h}$ is a sector s by year t fixed effect for $h+1$-year growth[8]. $\mathbf{1}\{\text{New Instrument} > 0\}_{j,t}$ is as an indicator variable that takes the value 1 if a firm raises funds using at least one novel instrument during the year t and zero otherwise, which means raising funds only with non-novel instruments. $Z_{j,t-1}$ is a vector of lagged firm-level controls, $\epsilon_{j,h,t+h}$ is a random error.

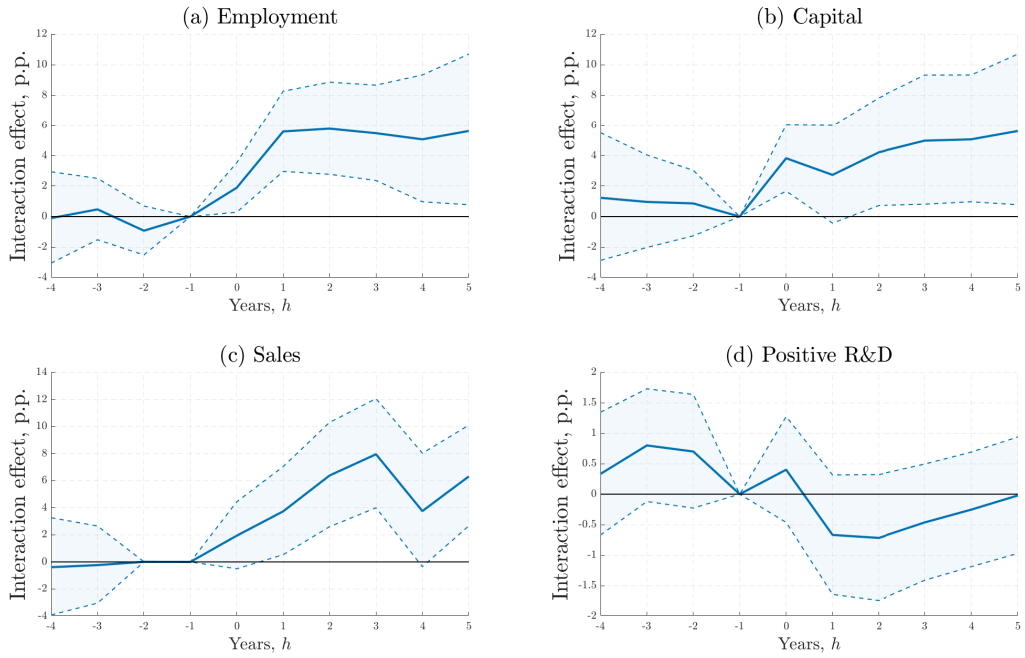
The main coefficient of interest, β^h, measures the difference in firm outcomes h years after raising funds using some novel instruments instead of only traditional ones. We multiply β^h by 100 to express the effect in percentage points.

Our baseline firm controls, $Z_{j,t-1}$, include standardized total assets, sales growth, the ratio of current to total assets, and leverage, all measured at the end of year $t-1$. These variables are included to account for observable differences that predict the firm's decision to use novel instruments (as shown in Section 3.4.2) and to mitigate concerns about endogeneity and omitted variable bias in estimating the effect of financing choices on firm outcomes.

Throughout the analysis, we cluster standard errors in two dimensions, by j and by t, to account for intra-unit and intra-time correlations.

[8]The sectors s we consider, based on SIC codes, are: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation communications, electric, gas, and sanitary services; wholesale trade; retail trade; and services. We do not include finance, insurance, and real estate, and utilities

Figure 3.9: Dynamics of firms' outcomes after raising funds using some novel instruments



Notes: Point estimates and 90% confidence intervals for β^h from estimating specification (3.4.2) for $h = \overline{-4, 5}$. Confidence intervals are based on two-way clustered standard errors at firm and time levels. Both point estimates and standard errors are scaled to percentage point units. The dependent variable $y_{j,t+h}$ includes the employment $l_{j,t+h}$, capital $k_{j,t+h}$, sales $s_{j,t+h}$ and the cumulative probability of positive R&D expenses $xrd_{j,t+h}$, defined as an indicator variable that takes the value 1 if a firm has positive R&D expenses between t and $t + h$ and zero otherwise.

Figure(3.9) presents our baseline findings. Panel (a) shows that raising funds through certain novel financial instruments is associated with a subsequent increase in employment. Firms that issue innovative instruments experience, on average, a 2 percentage point higher cumulative employment growth in the year of issuance compared to firms relying solely on standard instruments. This difference peaks at nearly 6 percentage points in year 2 and remains elevated through year 5. The effect is significant at the 90% level at the time of issuance and remains statistically significant at the 99% level thereafter.

Panel (b) examines the impact on capital. Similar to employment, firms raising funds with novel instruments experience, on average, a 3.7 percentage point higher increase in capital in the year of issuance compared to firms using standard instruments. This difference is statistically significant at the 99% level immediately after issuance. However, the effect decreases to 2.6 percentage points and becomes insignificant at the 90% level in the year

following the issuance. The effect then steadily increases, reaching 5.8 percentage points in year 5, and remains statistically significant at the 95% level from year 2 onwards.

Panel (c) shows the effect on sales. While the difference is initially small and insignificant, it grows to 7.8 percentage points three years after issuance, with statistical significance at the 99% level.

In contrast, as shown in Panel (d), we find no statistically significant difference in the probability of having positive R&D expenditures between firms that use novel financial instruments and those that rely on traditional instruments. This suggests that the decision to issue novel instruments does not affect the likelihood of engaging in R&D activities.

Across all outcomes, there is no statistically significant difference between the two groups of firms prior to the period of issuance.

3.5 Conclusion

This paper provides a detailed empirical account of financial innovation in U.S. capital markets, documenting the introduction and diffusion of over 8,500 distinct debt and equity instruments issued by non-financial firms between 1970 and 2020. We show that financial innovation is highly concentrated among larger, older firms and often responds to episodic shifts in regulation and macroeconomic conditions. While most new products remain niche, early adopters tend to experience faster subsequent growth in sales, investment, and employment. These patterns suggest that financial innovation may support firm expansion by offering more tailored or flexible financing options. Future work should build on these findings by developing structural models that endogenize firms' decisions to introduce new instruments and assess the broader implications for capital allocation and financial stability.

APPENDIX A

Appendix to Chapter 1

A.1 Monetary shock construction

Our baseline shock used in the firm-level analysis is based on the standard high-frequency-identified series of monetary policy surprises. We utilize the event-study methodology pioneered by cook1989 to measure surprise in monetary policy. Following Gurkaynak2005 we define a shock ε_t as:

$$\varepsilon_t = \tau(t) \times (\text{ffr}_{t+\Delta_+} - \text{ffr}_{t-\Delta_-}), \tag{A.1.1}$$

Here, t denotes the specific timing of the monetary announcement, while ffr_t denotes the implied Fed Funds Rate derived from a current-month Federal Funds futures contract at time t. The parameters Δ_+ and Δ_- determine the exact time window surrounding the announcement. The term $\tau(t)$ adjusts for the timing of the announcement within the month, defined as $\tau(t) \equiv \frac{\tau^n(t)}{\tau^n(t)-\tau^d(t)}$. In this formulation, $\tau^d(t)$ represents the day of the meeting in the month, and $\tau^n(t)$ denotes the total number of days in the month. Our focus is on a window where Δ_- is 15 minutes before the announcement and Δ_+ is 45 minutes after (labeled as 'wide'). We construct a moving average of the raw shocks, weighting them by the number of days remaining in the year (or quarter) after the shock occurs.

The sectoral-level exercise uses variation across NAICS industries. Since these have only been used since 2000, all data before 2000 are based on an imputation from the larger SIC categories. For this reason, we prefer to run this analysis inclusive of the post-2007 (zero-lower bound) period, to maximize the time that variation is not based on any imputation. However, we do not have access to the baseline series for this extended time period. Thus, for now, we use the 'target' shock from Swanson (2021) which extends the original methodology of Gurkaynak et al. (2005) to a longer sample. Gurkaynak et al. (2005) show that the effects

on a variety of asset prices can be well summarized by 2 factors: one that captures variation related to current short-term interest rates (especially current and next month federal funds futures) and a second one that is constrained to only load on future or longer-term interest rates (labeled the 'target' factor and the 'path' factor, respectively). Swanson (2021) extends this analysis to the post great-recession period (capturing 241 FOMC announcements from July 1991 to June 2019), adding a third factor to account for quantitative easing. We use the 'target' factor as identified by Swanson (2021) and (made publicly available) as the monetary policy shock in this paper, and sum over the quarter to aggregate the high-frequency shocks to a quarterly frequency.[1] This shock is designed to reflect variation in a variety[2] of asset prices, yet is primarily identified from movements of short-term interest rates (stripping away the forward guidance aspect of monetary policy). Consequently, it correlates very strongly with our baseline shock series: table A.1 shows that on the overlapping part of the sample the correlation between the baseline shock and the traget shock is 0.945.

Table A.1: Summary statistics of quarterly monetary policy shocks

	Raw High Frequency	Smoothed	Smoothed, +, sd 1	GSS target, +, sd 1
Mean	-0.0185	-0.0429	0.395	-0.112
Median	0	-0.0127	0.117	-0.303
S.D.	0.0855	0.108	1	0.820
Min	-0.463	-0.480	-2.149	-1.869
Max	0.152	0.233	4.430	4.679
Observations	164	71	71	111
Corr with (Smoothed, +, sd 1)	.	.	.	0.945

Note: Summary statistics of monetary policy shocks for the period 1/1/1990 to 12/31/2007. "High frequency" shocks are estimated using the event study strategy as in Ottonello and Winberry (2020). "Smoothed" shocks are time aggregated to a quarterly frequency using the weighted average. In the third column, shocks have a flipped sign to ease interpretation and are standardized. The last column summarize a series of 'target' shocks from Swanson (2021) based on the methodology of Gurkaynak et al. (2005) (flipped sign and standardized), which capture essentially the same variation for the main sample (as seen in the last cell of the table) and are available to us extended up till 2019. These are used in the sectoral quarterly analysis where most of the sources start only in 2000.

[1] As is standard in the literature, we exclude the FOMC announcement on September 17, 2001, which took place before markets opened but after financial markets had been closed for several days following the 9/11 terrorist attacks.

[2] Including federal funds futures contracts of different maturities, Eurodollar futures contracts of different maturities, and the 2-, 5-, and 10-year Treasury yields.

A.2 Firm Level data

This appendix outlines the procedures used to build the key variables and to define the sample of Compustat firm-year observations used in estimating equation 1.2.1.

A.2.1 Capital Stock Construction via the Perpetual Inventory Method

To measure firms' physical capital, we construct a real capital stock series using the perpetual inventory method (PIM) (see Mongey and Williams (2017)), rather than relying directly on the book value recorded in PPEGT. The procedure is implemented at the firm level as follows:

(i) Initial Capital Estimate: The series begins with the first non-missing value of PPEGT, which we treat as the initial capital stock k_{it} for firm i at time t.

(ii) Capital Update Rule: We update the capital stock recursively using the standard law of motion:

$$k_{it} = (1 - \delta)k_{i,t-1} + i_{it},$$

where δ is the depreciation rate and i_{it} denotes the firm's investment. Instead of directly observing investment, we recover it from changes in property, plant, and equipment (PPENT) as:

$$i_{it} = \text{PPENT}_{it} - \text{PPENT}_{i,t-1} + \delta k_{i,t-1}.$$

(iii) Addressing Missing Observations: If there are any gaps in the PPENT series during a firm's operating period, we fill them by linearly interpolating between adjacent non-missing values to maintain continuity in investment estimation.

(iv) Real Capital Adjustment: To obtain a measure of capital in real terms, we deflate net investment using the IPD (Nonfarm business sector: implicit price deflator, BEA-NIPA Table 1.3.4 Line 3) before applying it in the accumulation formula.

A.2.2 Other Variables construction

We construct the key variables employed in Section 1.2.2 as follows.

1. Leverage is measured as the ratio of total debt to total assets ($\text{ATQ}_{i,t}$). Total debt is calculated by summing the firm's short-term debt obligations and its long-term

liabilities, specifically $\text{DLCQ}_{i,t}$ (debt due within one year) and $\text{DLTTQ}_{i,t}$ (long-term debt).

2. We measure liquidity using the ratio of cash and cash equivalents to total assets, defined as $\text{CHEQ}_{i,t}/\text{ATQ}_{i,t}$, following Jeenas (2023).

3. We define firm age as the minimum of four available measures: the number of years since CRSP listing, since the IPO date, since the incorporation year reported in ritter2021initial, and since the firm's first appearance in the Annual Compustat database.

A.2.3 Sample Selection

Following the sample selection procedure in Ottonello and Winberry (2020), We apply several filters to the Compustat quarterly dataset. Specifically, We exclude all firm-year observations that meet any of the following criteria:

1. The firm is not incorporated in the United States.

2. The firm operates in the financial sector (SIC codes 6000–6999) or in utilities (SIC codes 4900–4999).

3. Key financial variables—total assets ($\text{ATQ}_{i,t}$, item 44), net property, plant, and equipment ($\text{PPENTQ}_{i,t}$, item 42), sales ($\text{SALEQ}_{i,t}$, item 2), or inventories ($\text{INVTQ}_{i,t}$, item 38)—are either missing or non-positive.

4. Measures of short-term debt ($\text{DLCQ}_{i,t}$, item 45), long-term debt ($\text{DLTTQ}_{i,t}$, item 51), or cash and short-term investments ($\text{CHEQ}_{i,t}$, item 38) are missing or recorded as negative values.

5. The observation precedes the firm's first available value for gross property, plant, and equipment ($\text{PPENTQ}_{i,t}$, item 118) across the full Compustat-annual panel.

6. The investment rate falls in the top or bottom 0.05 percent of its empirical distribution.

7. The firm's sales growth lies outside the interval $[-1, 1]$.

8. Leverage is not in the range $(0, 10]$.

9. The liquidity ratio is outside the interval $[-10, 10]$.

10. All subsequent firm-year observations are dropped once any of the above conditions are met, to ensure a consistent and comparable time series.

A.3 Additional Firm-Level Results

This section reports supplementary results that extend the main empirical analysis. The tables presented here provide further evidence on the immediate heterogeneous effects of monetary policy across firms, focusing on three key outcomes: investment, sales, and employment.

Table A.2: Heterogeneous investment responses to monetary policy

	(1)	(2)	(3)	(4)	(5)
leverage × ffr shock	-0.00218	-0.00463*	-0.00201		-0.00276
	(0.00174)	(0.00255)	(0.00218)		(0.00211)
leverage (with mean) × ffr shock				-0.00075	
				(0.00169)	
Observations	53079	53079	51593	51593	42849
R^2	0.268	0.268	0.309	0.309	0.273
Firm controls	no	no	yes	yes	yes
Interaction of leverage with L.GDP	no	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes
Spell of at least X years					yes
p-value on main coefficient	0.23	0.09	0.37	0.66	0.21

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is physical capital. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 and 2 omit the firm-level control variables. Column 1 omits the interaction of past GDP with past leverage. Column 4 reports the result for non-demeaned leverage. The last column restricts the sample to spells of at least 10 years of data on investment (a sample restriction adopted by Ottonello and Winberry (2020)). Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

Table A.3: Heterogeneous sales responses to monetary policy

	(1)	(2)	(3)	(4)	(5)
leverage × ffr shock	-0.00036	-0.00090	0.00042		0.00213
	(0.00232)	(0.00208)	(0.00207)		(0.00210)
leverage (with mean) × ffr shock				0.00069	
				(0.00240)	
Observations	52904	52904	51426	51426	42790
R^2	0.266	0.266	0.274	0.274	0.245
Firm controls	no	no	yes	yes	yes
Interaction of leverage with L.GDP	no	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes
Spell of at least X years					yes
p-value on main coefficient	0.88	0.67	0.84	0.78	0.32

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is sales. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 and 2 omit the firm-level control variables. Column 1 omits the interaction of past GDP with past leverage. Column 4 reports the result for non-demeaned leverage. The last column restricts the sample to spells of at least 10 years of data on investment (a sample restriction adopted by Ottonello and Winberry (2020)). Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

Table A.4: Heterogeneous capital-labor ratio responses to monetary policy

	(1)	(2)	(3)	(4)	(5)
leverage × ffr shock	-0.00591*	-0.00621	-0.00745*		-0.00663*
	(0.00331)	(0.00362)	(0.00395)		(0.00357)
leverage (with mean) × ffr shock				-0.01099***	
				(0.00339)	
Observations	51303	51303	49940	49940	42221
R^2	0.166	0.166	0.217	0.217	0.177
Firm controls	no	no	yes	yes	yes
Interaction of leverage with L.GDP	no	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes
Spell of at least X years					yes
p-value on main coefficient	0.09	0.11	0.08	0.01	0.08

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is capital intensity. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 and 2 omit the firm-level control variables. Column 1 omits the interaction of past GDP with past leverage. Column 4 reports the result for non-demeaned leverage. The last column restricts the sample to spells of at least 10 years of data on investment (a sample restriction adopted by Ottonello and Winberry (2020)). Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

A.4 Sector-Level Analysis

This appendix presents supplementary empirical results based on a sector-quarter panel dataset. The analysis parallels the firm-level regressions reported in the main text but is conducted at a higher level of aggregation, using industry-level data identified by 3-digit SIC codes. Our goal is to examine whether the heterogeneous effects of monetary policy on employment, sales, and physical capital observed at the firm level also appear in sectoral dynamics. We begin by describing the data sources and construction of the sector-quarter panel, and then report estimation results for each outcome variable.

A.4.1 Sector-Level Data

To conduct this analysis, we merge labor market data from the Quarterly Census of Employment and Wages (QCEW) with financial data from the Quarterly Financial Report (QFR).

QCEW (Quarterly Census of Employment and Wages): The QCEW, maintained by the U.S. Census Bureau, provides comprehensive coverage of private and public employers covered by unemployment insurance, with observations aggregated at the state and industry level using 3-digit NAICS codes. To ensure compatibility with the QFR, we restrict our sample to three major sectors: manufacturing, wholesale trade, and retail trade. From the QCEW, we extract total employment, total wages, and average weekly wages as our primary labor market measures. Summary statistics for these variables are reported in Table A.5.

The sectoral QCEW employment data aligns with the firm-level data (Table 1.2) in terms of the mean and median employment growth but exhibits five times less variation, as expected given the aggregation.

QFR (Quarterly Financial Report): The QFR data offers aggregate statistics on the financial status of U.S. corporations prepared by the Census Bureau. Derived from a sample survey, the QFR provides estimated income statements, retained earnings statements, balance sheets, and associated financial and operating ratios. An advantage of the dataset is its coverage of publicly traded and privately held firms. It covers manufacturing corporations with assets of $250,000 and above, as well as wholesale trade and retail trade corporations with assets of $50 million and above. The aggregate statistics are available by industry and asset size. Prior to 2000, the data is only available for industries at the 2-digit SIC code level;

Table A.5: Summary statistics of QCEW state-sector data

	e_{jt}	$\Delta \log e_{jt}$	$w \cdot e_{jt}$	$\Delta \log w \cdot e_{jt}$	w_{jt}	$\Delta \log w_{jt}$
Mean	1012542.7	-0.004	8.64e+09	0.006	654.118	0.010
Median	805680.6	-0.001	6.66e+09	0.009	615.006	0.011
S.D.	601733.1	0.023	5.95e+09	0.035	290.687	0.036
5th Percentile	191009.7	-0.028	1.98e+09	-0.041	251.870	-0.029
95th Percentile	2063046.8	0.012	2.03e+10	0.049	1235.191	0.046
Observations	1913.0	1913.000	1913.00	1913.000	1913.000	1913.000

Summary statistics of sector-level variables in QCEW sample in 1990-2007.

since 2000, the data is available at the 3-digit NAICS code levels. We construct the same variables used in the firm-level analysis with Compustat: leverage, sales growth, size, current assets. The sales data in QFR come seasonally adjusted (using X-12-ARIMA method by the U.S. Census Bureau). The rest of the variables are balance sheet variables.

Table A.6 presents summary statistics of the relevant financial variables for sectors matched with QCEW data for the period 1990-2007, with the final sample of 25 sectors over 106 quarters. Sectoral-level data on leverage mimics well the firm-level Compustat data in terms of the mean and median.[3]

Table A.6: Summary statistics of QFR sector-level data

	ℓ_{jt}	$\Delta \log k_{jt+1}$
Mean	0.291	-0.002
Median	0.293	-0.001
S.D.	0.072	0.060
5th Percentile	0.169	-0.031
95th Percentile	0.403	0.033
Observations	1913.000	1913.000

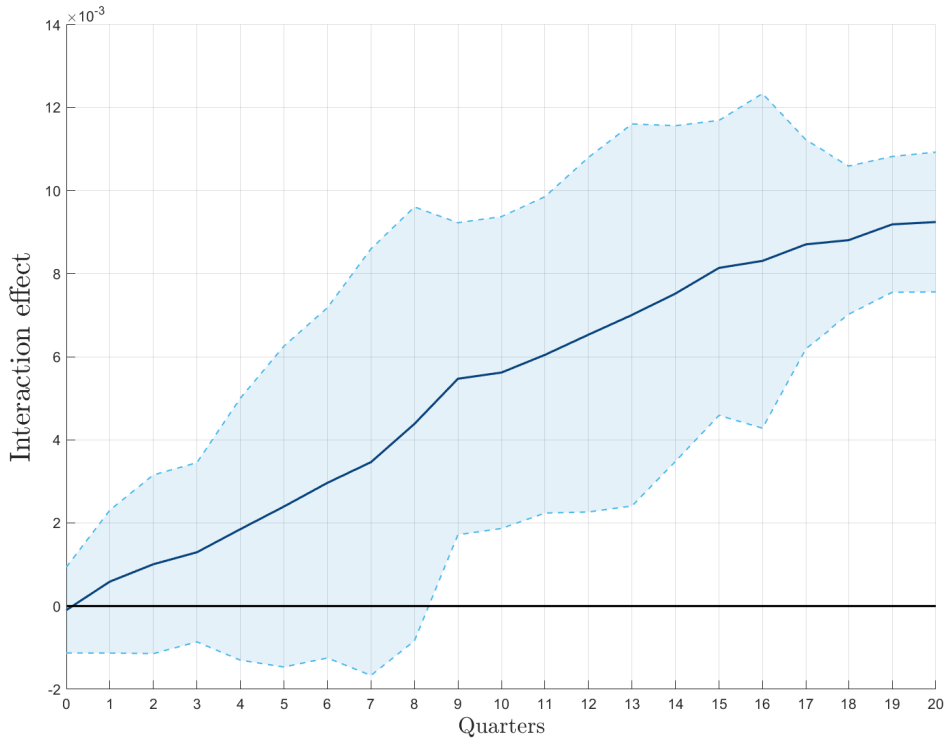
Summary statistics of sector level variables in QFR sample. ℓ_{jt} is the debt-to-asset ratio and $\Delta \log k_{jt+t}$ is the log change in the book value of tangible capital stock. The sample is a set of sectors matched with QCEW data for the period 1990-2007.

[3]As is expected for a more aggregated series, both leverage and $\Delta \log k$ exhibit far less variation in the sectoral panel.

A.4.2 Sector-Level Results

Here we present results using simple sectoral variation. Specifically, we run the regression specified in equation 1.2.1 with j a 3-digit NAICS sector and t quarterly time, α_τ are simply time fixed effects. The vector $Z_{j,t-1}$ includes leverage $\ell_{j,t-1}$, total assets, sales growth, current assets as a proportion of total assets at the sector level, as well as the interaction of $\ell_{j,t-1}$ with the previous year's GDP growth and unemployment rate to control for differences in firms' cyclical sensitivities.

Figure A.1: Response of employment to a monetary shock, sector level



Notes: This figure shows the estimated dynamic interaction coefficient β^h between leverage and monetary policy shocks over a twenty-quarter horizon ($h = \overline{0, 20}$). The dependent variable $y_{j,t+h}$ is employment, measured at the 3-digit NAICS sector level. Estimates are based on the regression specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{\tau,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in Section 1.2.3 of the main text. Dashed lines represent 95% confidence intervals, constructed using two-way clustered standard errors at the sector and quarter.

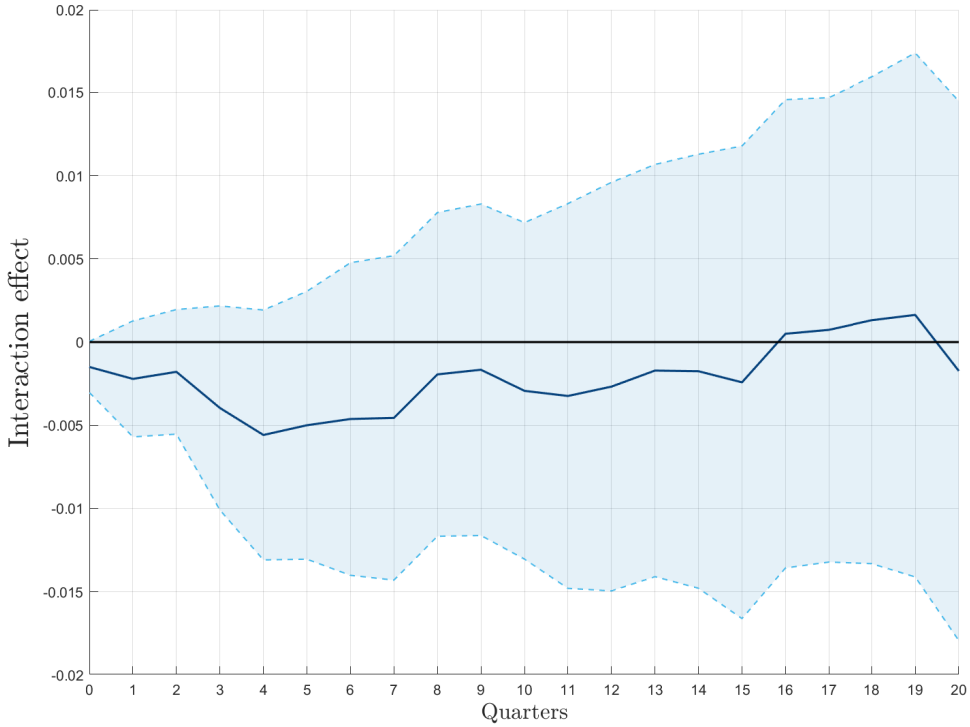
Figure A.1 shows the differential in the impulse response of employment for each horizon $h \in \overline{0, 20}$. A surprise in monetary policy towards easing leads to a stronger employment ex-

pansion in sectors with higher prior leverage. Specifically, a one standard deviation change in the monetary shock results in a 0.5 percentage point increase in employment in sectors with one standard deviation more leverage observed nine quarters after the shock (p-value = 0.01). This effect is persistent, lasting up to 20 quarters post-shock. These findings are consistent with recent evidence by Bahaj et al. (2022) and our firm-level evidence, demonstrating that employment in financially constrained firms responds more strongly to monetary policy shocks.

We also test for the differential response of capital investment and sales as the dependent variable. Figure A.2 confirms that the shape of the impulse response functions matches Ottonello and Winberry (2020) with more leveraged sectors expanding their investment less in response to an easing of monetary policy, even though the results are insignificant. Figure A.3 shows sales of leveraged sectors might be more sensitive to monetary policy, although the effect is very imprecisely estimated.

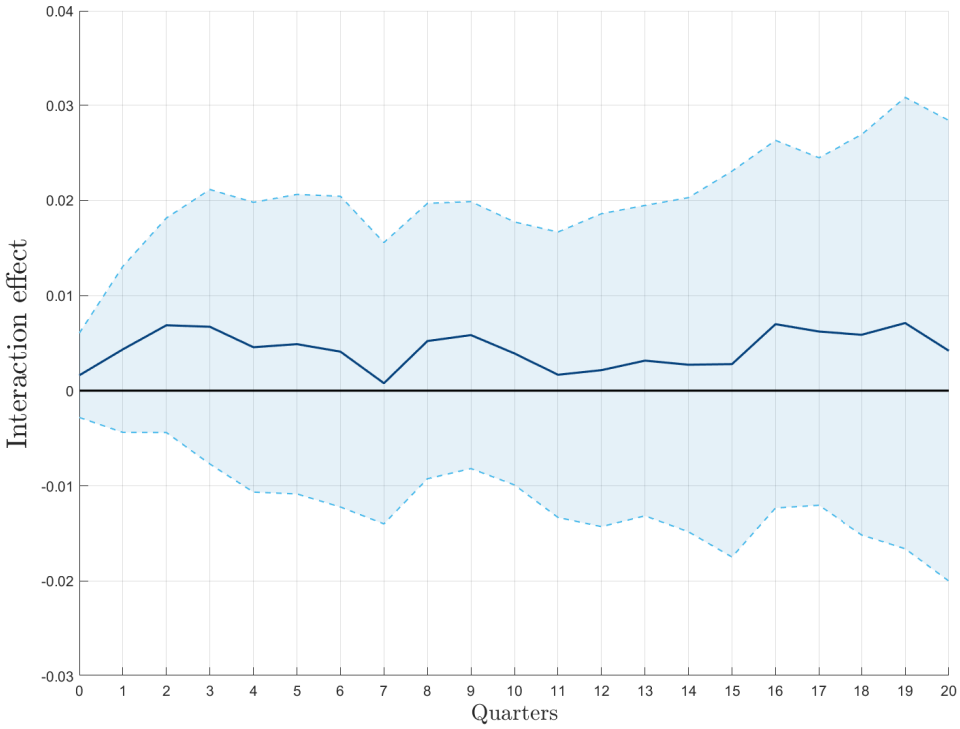
Figure A.4 presents the dynamic response of average wages to a monetary policy shock at the sector level. We observe a slight decline in wages following an expansionary monetary shock, consistent with a labor market reallocation toward lower-paid jobs or sectors. While the estimated effect is economically meaningful in magnitude, it is imprecisely estimated, and the confidence intervals include zero throughout most of the horizon.

Figure A.2: Response of capital to a monetary shock, sector level



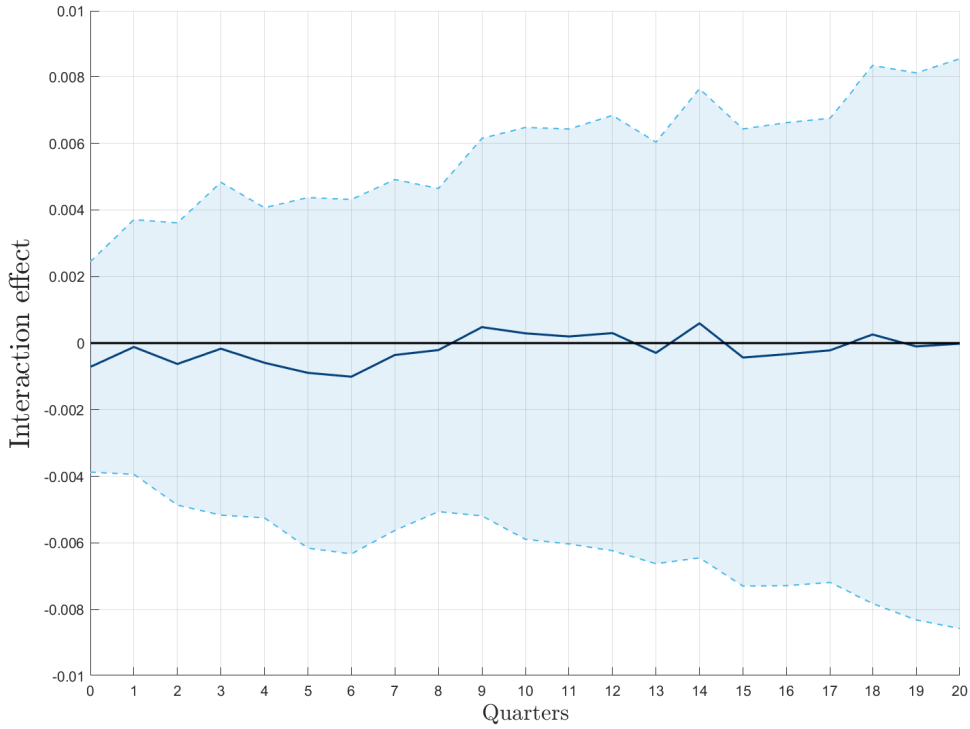
Notes: This figure shows the estimated dynamic interaction coefficient β^h between leverage and monetary policy shocks over a twenty-quarter horizon ($h = \overline{0, 20}$). The dependent variable $y_{j,t+h}$ is physical capital, measured at the 3-digit NAICS sector level. Estimates are based on the regression specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{\tau,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in Section 1.2.3 of the main text. Dashed lines represent 95% confidence intervals, constructed using two-way clustered standard errors at the sector and quarter.

Figure A.3: Response of sales to a monetary shock, sector level



Notes: This figure shows the estimated dynamic interaction coefficient β^h between leverage and monetary policy shocks over a twenty-quarter horizon ($h = \overline{0, 20}$). The dependent variable $y_{j,t+h}$ is sales, measured at the 3-digit NAICS sector level. Estimates are based on the regression specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{\tau,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in Section 1.2.3 of the main text. Dashed lines represent 95% confidence intervals, constructed using two-way clustered standard errors at the sector and quarter.

Figure A.4: Response of average wages to a monetary shock, sector level



Notes: This figure shows the estimated dynamic interaction coefficient β^h between leverage and monetary policy shocks over a twenty-quarter horizon ($h = \overline{0, 20}$). The dependent variable $y_{j,t+h}$ is average wage, measured at the 3-digit NAICS sector level. Estimates are based on the regression specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{\tau,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in Section 1.2.3 of the main text. Dashed lines represent 95% confidence intervals, constructed using two-way clustered standard errors at the sector and quarter.

A.5 Robustness Checks

A.5.1 Alternative monetary policy shocks

We begin by examining whether our findings hold when using different measures of monetary policy. Table A.7 in Appendix A.5.3 presents the results for the log changes in employment, capital stock, and capital intensity across various shock measures drawn from the literature. The results are broadly consistent across alternative measures.

First, we replicate the baseline firm-level analysis using the target shock from Swanson (2021). The results are broadly consistent, with column 2 indicating that any differences stem from sample coverage rather than the shock itself.

The strategy of using high-frequency surprises as monetary policy shocks has been the subject of much scrutiny. Several studies argue that these shocks may capture more than just changes in monetary policy orthogonal to current economic conditions. To mitigate these concerns, various authors have proposed methods to orthogonalize high-frequency surprises with respect to the information effect.

Our results remain robust across alternative shocks, with few notable exceptions. The Romer and Romer (2004) series, extended by Wieland and Yang (2020) through 2012Q4, and Aruoba and Drechsel (2024), which utilizes natural language processing on Federal Reserve documents, show similar effects on employment, though these estimates are less precise. In contrast, the effects on capital investment are negligible.

A.5.2 Robustness to controlling for the shock interacted with firm-level controls

We verify that our baseline results on the impact of firm leverage in response to monetary policy shocks are not confounded by other firm characteristics. Specifically, we examine whether the estimated effects are driven by differences across firm size, growth rates, or liquidity, proxied by the share of current assets in total assets. Across all outcomes – employment, capital, and the capital-labor ratio – the central role of leverage remains robust (see Tables A.8, A.9, and A.10).

Table A.10 also provides suggestive evidence that large and growing firms tend to increase their capital intensity more than others during monetary policy easing episodes. This pattern may reflect differences in financial flexibility: firms with better access to external financing may respond to policy loosening by expanding investment rather than employment.

Table A.7: Firm-level results with alternative MP shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					$\Delta \log k_{jt+1}$				
lev × mp shock	-0.0046**	-0.0036	-0.0050***	-0.0050**	-0.0029**	-0.0030*	-0.0016	0.0017	0.0002
	(0.0020)	(0.0022)	(0.0016)	(0.0020)	(0.0012)	(0.0016)	(0.0018)	(0.0021)	(0.0015)
p-value	0.03	0.11	0.01	0.03	0.02	0.07	0.38	0.41	0.91
Observations	49516	40146	47112	37729	59610	42849	45438	89773	64978
R^2	0.256	0.281	0.263	0.287	0.243	0.273	0.270	0.229	0.253
					$\Delta \log e_j$				
lev × mp shock	0.0040	0.0057*	0.0032	0.0058*	0.0023	0.0056*	0.0062***	0.0042	0.0042
	(0.0026)	(0.0028)	(0.0025)	(0.0028)	(0.0021)	(0.0029)	(0.0021)	(0.0026)	(0.0031)
p-value	0.14	0.06	0.22	0.05	0.29	0.07	0.01	0.11	0.19
Observations	48768	39571	46361	37151	58644	42221	44753	88450	63941
R^2	0.215	0.232	0.218	0.233	0.200	0.222	0.219	0.174	0.196
					$\Delta \log \frac{k_{jt}}{e_{jt}}$				
lev × mp shock	-0.0058**	-0.0066*	-0.0075**	-0.0092**	-0.0039*	-0.0072**	-0.0064***	-0.0039	-0.0040
	(0.0027)	(0.0032)	(0.0033)	(0.0038)	(0.0021)	(0.0026)	(0.0022)	(0.0032)	(0.0032)
p-value	0.05	0.06	0.04	0.03	0.07	0.02	0.01	0.22	0.23
Observations	48768	39571	46361	37151	58644	42221	44753	88450	63941
R^2	0.169	0.184	0.173	0.189	0.156	0.177	0.174	0.134	0.153
Baseline sample		yes		yes		yes			
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Spells >= 10 y	yes	yes	yes	yes	yes	yes	yes	yes	yes
MP shock	Swanson 2021 (target)	Swanson 2021 (target)	Jarocinsky & Karadi	Jarocinsky & Karadi	Bauer & Swanson	Bauer & Swanson	Miranda-Agrippino & Ricco	Romer & Romer extended	Arouba & Drechsel

Notes: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$, using the alternative definitions of shocks. All control variables are defined in the main text (Section 1.2.3). Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. The reported p-value corresponds to the main effect of interest.

Table A.8: Robustness: shock interacted with firm-level controls– employment

	(1)	(2)	(3)	(4)
leverage × ffr shock	0.00550**	0.00547**	0.00518*	0.00540*
	(0.00258)	(0.00256)	(0.00246)	(0.00261)
size × ffr shock		0.00083		
		(0.00184)		
sales growth × ffr shock			-0.00369	
			(0.00304)	
Share of current assets × ffr shock				-0.00090
				(0.00159)
Observations	49940	49940	49940	49940
R^2	0.261	0.261	0.261	0.261
Firm controls	yes	yes	yes	yes
Interaction of leverage with L.GDP	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes
p-value on main coefficient	0.05	0.05	0.05	0.06

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is employment. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 is baseline specification. Column 2,3 and 4 include additional control interacting sales, sales growth and hare of current assets in total assets with baseline monetary shock respectively. Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

Table A.9: Robustness: shock interacted with firm-level controls – capital

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.00201	-0.00205	-0.00220	-0.00219
	(0.00218)	(0.00216)	(0.00219)	(0.00217)
size × ffr shock		0.00193		
		(0.00213)		
sales growth × ffr shock			-0.00240	
			(0.00253)	
Share of current assets × ffr shock				-0.00194
				(0.00190)
Observations	51593	51593	51593	51593
R^2	0.309	0.309	0.309	0.309
Firm controls	yes	yes	yes	yes
Interaction of leverage with L.GDP	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes
p-value on main coefficient	0.37	0.36	0.33	0.33

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is physical capital. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 is baseline specification. Column 2,3 and 4 include additional control interacting sales, sales growth and hare of current assets in total assets with baseline monetary shock respectively. Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

Table A.10: Robustness: shock interacted with firm-level controls – capital intensity

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.00745*	-0.00763*	-0.00660*	-0.00728*
	(0.00395)	(0.00392)	(0.00375)	(0.00399)
size × ffr shock		0.00613*		
		(0.00298)		
sales growth × ffr shock			0.00997**	
			(0.00431)	
Share of current assets × ffr shock				0.00168
				(0.00271)
Observations	49940	49940	49940	49940
R^2	0.217	0.217	0.218	0.217
Firm controls	yes	yes	yes	yes
Interaction of leverage with L.GDP	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes
p-value on main coefficient	0.08	0.07	0.10	0.09

Note: Results from estimating variants of the baseline specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, for $h = 0$. The dependent variable $y_{j,t+h}$ is capital-labor ratio. Point estimates and standard errors are reported in log units. All control variables are defined in the main text, Section 1.2.3. Columns 1 is baseline specification. Column 2,3 and 4 include additional control interacting sales, sales growth and hare of current assets in total assets with baseline monetary shock respectively. Standard errors in parentheses are clustered two ways, on firm and year. The last row of the table reports the p-value on the main effect of interest.

A.5.3 Robustness to Controls Motivated by Prior Literature

Relation to Ottonello and Winberry (2020) and Distance to Default: As a robustness exercise, we follow Ottonello and Winberry (2020) and construct a measure of distance to default to capture firm-level financial conditions. The construction follows the approach in Gilchrist et al. (2012), using firm equity, liabilities, and volatility to approximate a structural default threshold. We interact this measure with monetary policy shocks to assess whether our baseline findings are sensitive to alternative measures of financial health. The results, reported below for employment, capital, sales, and capital-labor ratio in Figure A.5, confirm that the key patterns documented in the main text are broadly preserved under this alternative specification. The strongest differential response is observed for capital intensity: firms further from default increase their capital-labor ratio by approximately 2 percentage points more than their more financially constrained counterparts within two years following an expansionary monetary policy shock.

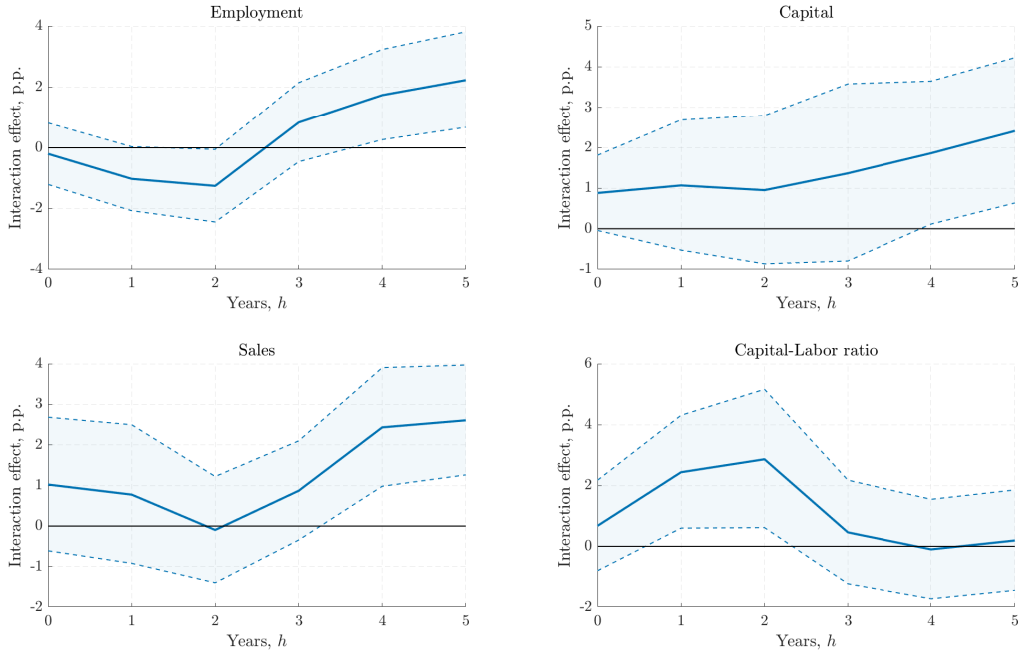
Relation to Jeenas (2023) and liquidity: Jeenas (2023) shows that differences in liquidity (which are correlated with leverage) matter for heterogenous responses of firms to monetary policy. Here we show that our conclusions are robust to accounting for differences in liquidity in our main specifications. Figure A.6 shows the results of running the baseline firm-level regressions, adding a within-firm measure of liquidity as a control.

$$\begin{aligned}\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \gamma^h(\mathcal{L}_{j,t-1} - \mathbb{E}_j[\mathcal{L}_{j,t}])\varepsilon_t^m \\ + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \Delta^h(\mathcal{L}_{j,t-1} - \mathbb{E}_j[\mathcal{L}_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}, \quad \text{(A.5.1)}\end{aligned}$$

The effect of leverage on capital-labor substitution after a monetary policy shock is effectively unchanged when differences in liquidity are accounted for.

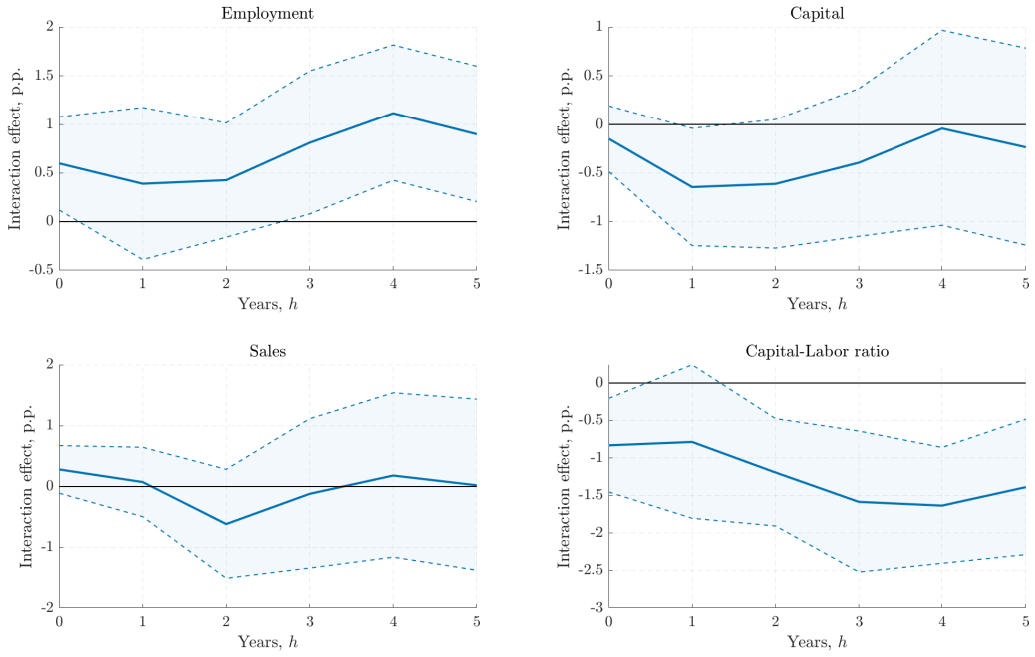
Jeenas (2023) also argue that low-leverage firms are in fact less responsive to monetary policy over longer horizons in their capital investment, the opposite of the conclusion in Ottonello and Winberry (2020). Part of the difference comes from focusing on a different time horizon (Jeenas (2023) shows results for several years after the policy shock). Moreover, Ottonello and Winberry (2020) show low-leverage firms' investment is more sensitive only when leverage is not demeaned within firm–i.e. when the conclusion relies on permanent differences across firms. However, these are very possibly correlated with many other permanent differences across firms (in their business models, production modes, permanent

Figure A.5: Heterogeneous responses to monetary policy by distance to default



Notes: This figure displays the dynamic interaction coefficient β^h between distance to default and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variables $y_{j,t+h}$ are employment, physical capital, sales and capital intensity. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(d2d_{j,t-1} - \mathbb{E}_j[d2d_{j,t}])\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(d2d_{j,t-1} - \mathbb{E}_j[d2d_{j,t}])Y_{t-1} + \epsilon_{j,h,t+h}$, where all variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

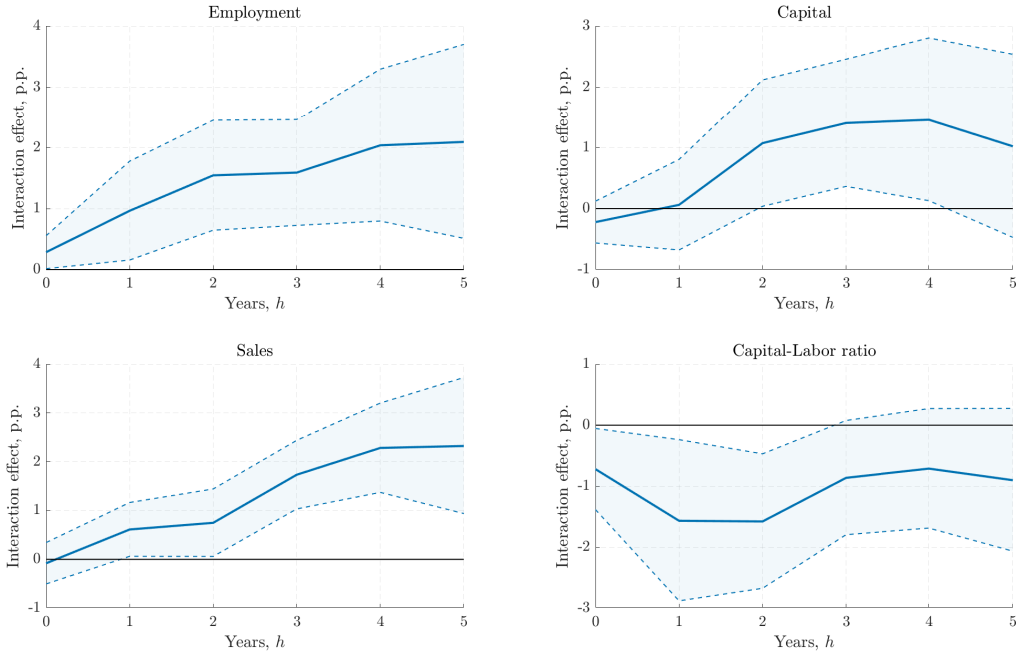
Figure A.6: Heterogeneous responses to monetary policy – controlling for firm liquidity



Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variables $y_{j,t+h}$ are employment, physical capital, sales and capital intensity. Estimates are obtained from the specification A.5.1 where all other variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

productivity etc.). In contrast, when leverage is measured within firm, those who find themselves in a less-leveraged point in their lifecycle are robustly more sensitive to monetary policy in investment. Bellow we reproduce our baseline results, using raw $\ell_{j,t-1}$ instead of $(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])$. Indeed, figure A.7 shows that when the variation in leverage does include permanent differences across firms, leveraged firms react more to monetary policy. This is true for capital, but is even more so for labor. Thus, the conclusion that leveraged firms substitute towards labor from capital after easing of monetary policy is robust to the measure used by Jeenas (2023).[4]

Figure A.7: Heterogeneous responses to monetary policy – leverage in levels



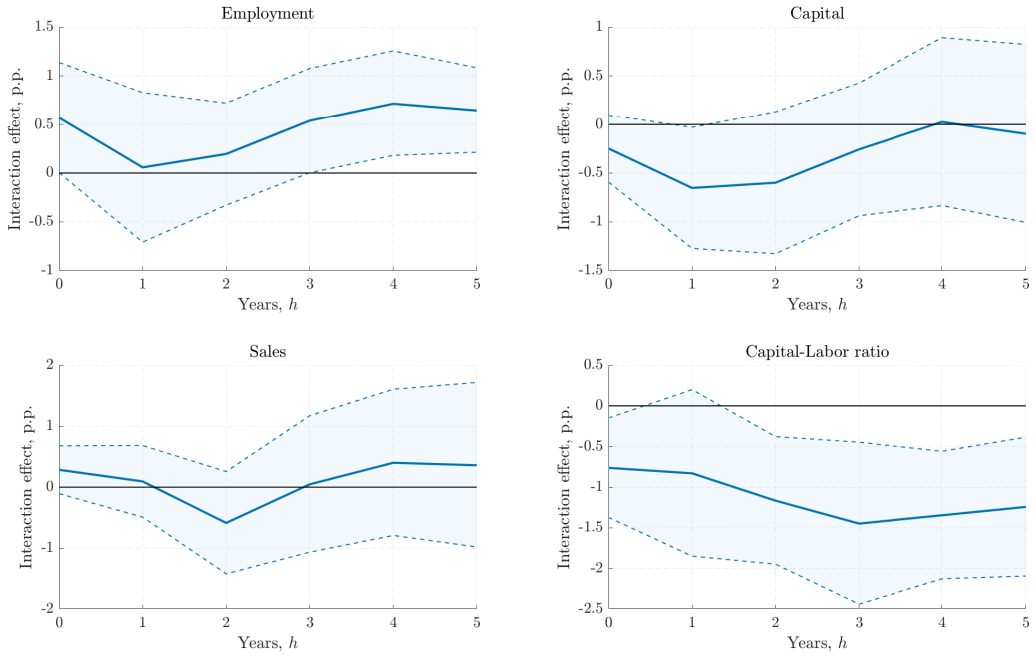
Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variables $y_{j,t+h}$ are employment, physical capital, sales and capital intensity. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h \ell_{j,t-1}\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h' \ell_{j,t-1} Y_{t-1} + \epsilon_{j,h,t+h}$, where all other variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

[4]Jeenas (2023) also trim the data on leverage more aggressively, getting rid of the top 1%. We drop observations with over 1000% leverage and then winsorize the top 0.5%. Shaving another 1% of most leveraged observations from the sample does not change any qualitative conclusions, but makes estimates less precise. This is not surprising given that theory predicts that the firms closest to being constrained are the ones relevant for the mechanism.

Relation to Cloyne et al. (2023) and firm age: Following Cloyne et al. (2023), we examine whether our baseline results are sensitive to firm age by allowing monetary policy shocks to interact with firm-level age measure. We define firm age as the minimum of four available indicators: the number of years since CRSP listing, since the IPO date, since the incorporation year reported in Ritter (2021), and since the firm's first appearance in the Annual Compustat database.

The results, shown in Figure A.8, indicate that controlling for firm age does not alter our main findings. The heterogeneity in responses by leverage remains stable across all outcome variables, suggesting that firm age is not a confounding factor in the transmission of monetary policy in our setting.

Figure A.8: Heterogeneous responses to monetary policy – controlling for firm age



Notes: This figure displays the dynamic interaction coefficient β^h between leverage and monetary policy shocks over a five-year horizon $h = \overline{0,5}$. The dependent variables $y_{j,t+h}$ are employment, physical capital, sales and capital intensity. Estimates are obtained from the specification $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \alpha_{s,t,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \gamma^h \text{Age}_{j,t-1}\varepsilon_t^m + \Gamma_h' Z_{j,t-1} + \Omega_h'(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])Y_{t-1} + \Delta^h \text{Age}_{j,t-1} Y_{t-1} + \epsilon_{j,h,t+h}$, where all other variables are defined in the main text, Section 1.2.3. The figure plots point estimates and 90% confidence intervals, constructed using standard errors clustered at both the firm and time levels. All estimates are scaled to percentage point units.

APPENDIX B

Appendix to Chapter 2

B.1 Details on the model

B.1.1 Firm problem and optimality conditions

We first set up the firm problem, using the representation of the penalty function for the constraints of the dividend and the collateral. The objective of both firm types $j \in \{A, B\}$ is to maximize the expected stream of dividends, discounted at its owner's discount factor $m_{t,t+1}$.

$$\max_{n_t^j(i),k_{t+1}^j(i),b_{t+1}^j(i)} E_0 \sum_{t=0}^{\infty} m_{0,t} d_t^j(i) \tag{B.1.1}$$

subject to

$$d_t^j(i) = d_t^{0j}(i) - \Psi_t^{dj}(i) - \Psi_t^{bj}(i) \tag{B.1.2}$$

$$d_t^{0j}(i) = p_t^j x(k_t^j(i), n_t^j(i)) - w_t n_t^j(i) - Q_t[k_{t+1}^j(i) - (1-\delta)k_t^j(i)] - Q_t \cdot AC(k_{t+1}^j(i), k_t^j(i)) - \frac{b_t^j(i)}{\pi_t} + \frac{b_{t+1}^j(i)}{R_t} \tag{B.1.3}$$

$$\Psi_t^{dj}(i) = \frac{1}{\chi} \exp\big(-\chi d_t^{0j}(i)\big) \tag{B.1.4}$$

$$\Psi_t^{bj}(i) = \frac{1}{\chi} \exp\big(\chi[b_{t+1}^j(i) - \theta E_t \pi_{t+1} Q_{t+1} k_{t+1}^j(i)]\big) \tag{B.1.5}$$

For both firm types $j \in \{A, B\}$, the optimality conditions with respect to

$b^j_{t+1}(i), k^j_{t+1}(i), n^j_t(i)$ are

$$b^j_{t+1}(i) : \frac{1}{R_t} - \frac{\partial \Psi^{dj}_t(i)}{\partial b^j_{t+1}} - \frac{\partial \Psi^{bj}_t(i)}{\partial b^j_{t+1}} - E_t m_{t,t+1} \frac{1}{\pi_{t+1}} - E_t m_{t,t+1} \frac{\partial \Psi^d_{t+1}{}^j(i)}{\partial b^j_{t+1}} = 0 \tag{B.1.6}$$

$$n^j_t(i) : p^j_t x'_n(k^j_t(i), n^j_t(i))^j - \frac{\partial \Psi^{dj}_t(i)}{\partial n^j_t} - w_t = 0 \tag{B.1.7}$$

$$k^j_{t+1}(i) : Q_t = -Q_t \cdot AC'_1(k^j_{t+1}(i), k^j_t(i)) - \frac{\partial \Psi^{dj}_t(i)}{\partial k^j_{t+1}} - \frac{\partial \Psi^{bj}_t(i)}{\partial k^j_{t+1}} +$$

$$E_t m_{t,t+1} \Bigg[p^j_t x'_k(k^j_{t+1}(i), n^j_{t+1}(i)) + Q_{t+1}(1-\delta) - Q_{t+1} AC'_2(k^j_{t+2}(i), k^j_{t+1}(i)) - \frac{\partial \Psi^d_{t+1}{}^j(i)}{\partial k^j_{t+1}} \Bigg] \tag{B.1.8}$$

$$\frac{\partial \Psi^{bj}_t(i)}{\partial b^j_{t+1}} = \chi \Psi^{bj}_t(i) \tag{B.1.9}$$

$$\frac{\partial \Psi^{bj}_t(i)}{\partial k^j_{t+1}} = -\chi \theta^j E_t \pi_{t+1} Q_{t+1} \Psi^{bj}_t(i) \tag{B.1.10}$$

$$\frac{\partial \Psi^{dj}_t(i)}{\partial n^j_t} = \chi w^j_t \Psi^{dj}_t(i) \tag{B.1.11}$$

$$\frac{\partial \Psi^{dj}_t(i)}{\partial b^j_{t+1}} = -\chi \frac{1}{R_t} \Psi^{dj}_t(i) \tag{B.1.12}$$

$$\frac{\partial \Psi^d_{t+1}{}^j(i)}{\partial b^j_{t+1}} = \chi \frac{1}{\Pi_{t+1}} \Psi^d_{t+1}{}^j(i) \tag{B.1.13}$$

$$\frac{\partial \Psi^{dj}_t(i)}{\partial k^j_{t+1}} = \chi Q_t [1 + AC'_1(k^j_{t+1}(i), k^j_t(i))] \Psi^{dj}_t(i) \tag{B.1.14}$$

$$\frac{\partial \Psi^d_{t+1}{}^j(i)}{\partial k^j_{t+1}} = \chi Q_{t+1} [-(1-\delta) + AC'_2(k^j_{t+2}(i), k^j_{t+1}(i))] \Psi^d_{t+1}{}^j(i) \tag{B.1.15}$$

B.1.2 Steady state

B.1.2.1 Household problem

$$\text{Labor supply} \quad \frac{U_n(c,n)}{U_c(c,n)} = -w \tag{B.1.16}$$

$$\text{Budget constraint} \quad c = wL + (b - \frac{b}{1+r^n}) + d - T \tag{B.1.17}$$

B.1.2.2 Prices

$$\text{Stochastic discount factor} \quad m = \beta \tag{B.1.18}$$

$$\text{Bond supply} \quad \frac{1}{1+r^n} = \beta \tag{B.1.19}$$

$$\text{Capital price} \quad Q = 1 \tag{B.1.20}$$

$$\text{Gross interest rate} \quad R = 1 + (1-\tau)r^n \tag{B.1.21}$$

$$\text{Markup} \quad \mathcal{M} = \eta \tag{B.1.22}$$

$$\text{Wholesale prices} \quad p^j = \big(\frac{y}{x^j}\big)^{\frac{1}{\kappa}} \frac{1}{\mathcal{M}} \tag{B.1.23}$$

B.1.2.3 Firm problem

$$\Psi^{dj} = \frac{1}{\chi^d} \exp\left(\chi^d(\omega-1)d^j\right), \tag{B.1.24}$$

$$\Psi^{bj} = \left(\frac{1}{R} - \beta\right)\left(1 + \chi^d \Psi^{dj}\right)\frac{1}{\chi^b}, \tag{B.1.25}$$

$$b^j = \frac{\log\left(\chi^b \Psi^{bj}\right)}{\chi^b} + (1-\delta)\theta k^j, \tag{B.1.26}$$

$$n^j = \left[\frac{w}{\nu(1-\alpha)p^j (x^j)^{(\nu+\rho)/\nu}}\right]^{\frac{1}{-\rho-1}}, \tag{B.1.27}$$

$$d^j = p^j x^j - wL^j - Q\cdot\left(k^j - (1-\delta)k^j\right) - b^j + \frac{b^j}{R}, \tag{B.1.28}$$

$$0 = \beta\nu\alpha p^j (k^j)^{-\rho-1}(x^j)^{\frac{\nu+\rho}{\nu}} - \left(1 - \beta(1-\delta) - (1-\delta)\theta\left(\frac{1}{R} - \beta\right)\right), \tag{B.1.29}$$

$$x^j = \left(\alpha(k^j)^{-\rho} + (1-\alpha)(L^j)^{-\rho}\right)^{\frac{-\nu}{\rho}}. \tag{B.1.30}$$

B.1.2.4 Aggregation

$$y = x^j \tag{B.1.31}$$

$$L = n^j \tag{B.1.32}$$

$$K = k^j \tag{B.1.33}$$

$$B = b^j \tag{B.1.34}$$

$$C = y - \delta K \tag{B.1.35}$$

$$T = (\frac{1}{R} - \frac{1}{1+r_n})B \tag{B.1.36}$$

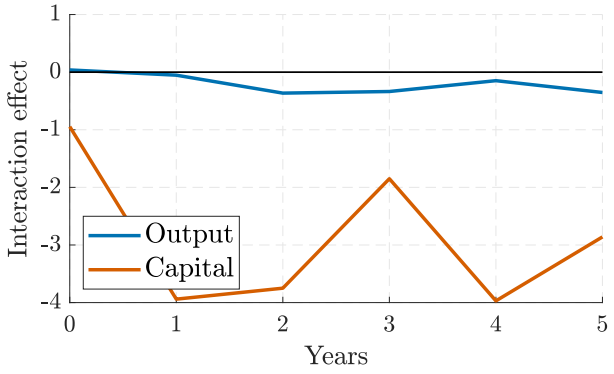
B.2 Firms' output and capital path dependence

While our model matches qualitatively the patterns observed in the data, the quantitative response is not comparable. First, if the variation in leverage in the model was to be taken literally as having the same effect on financial constraints in the data, the differential response of capital in B.1 was many orders of magnitude too large. This is not surprising. The firm heterogeneity in our model is by design set up to illustrate the role of binding versus lax

financial constraints, while using only very small shocks (a requirement of the perturbation method). Thus, a tiny variation in leverage has to translate to a large variation in how binding financial constraints are, so it would affect behavior. In contrast, the link in the data between leverage and the severity of financial constraints is bound to be much weaker. For this reason, the model is not well suited for quantitative comparisons across firms.

Second, while in the empirical analysis the differential response of capital and labor are similar in magnitude (in absolute terms), our mechanism can only generate a labor demand response that is weaker than the capital demand response. This is a limitation of our approach and suggests that other mechanisms influencing a differential response of employment might be in play.

Figure B.1: The Dynamics of capital and output's differential response to monetary shocks by the firm's leverage



Notes: Estimating equation $\Delta_h \log y_{j,t+h} = \alpha_{j,h} + \beta^h(\ell_{j,t-1} - \mathbb{E}_j[\ell_{j,t}])\varepsilon_t^m + \epsilon_{j,h,t+h}$ for $h = \overline{0,5}$ on simulated data without controls. The dependent variable $y_{j,t+h}$ is firm output. The standard errors are clustered at the firm and economy levels. A panel of 100 economies with 900 periods. y-axis values are in units of standard deviation of σ_{ε^m}

APPENDIX C

Appendix to Chapter 3

C.1 Construction of the SDC Platinum Transaction Sample

We clean SDC as follows:

1. Package Deals: Certain instruments are issued together in a package, featuring the same characteristics but with the total offering amount divided across multiple deal IDs.
   Our approach: For each package and issuer, we identify transactions that share the same offering date, maturity date, coupon features, principal amounts offered, and proceeds raised across all markets. We then aggregate the principal and proceeds for each market and retain only one record per grouping.

2. Multiple Issuers in a Single Package: Some deal packages involve multiple issuers, each assigned a different 6-digit CUSIP but sharing a common package ID.
   Our approach: We exclude any packages with multiple issuers.

3. Multiple Deal IDs for the Same Transaction: In some cases, deals appear multiple times with identical 9-digit CUSIP, same 6-digit CUSIP, offering date, and maturity date but differing deal IDs. These occurrences are common among financial institutions and federal agencies.
   Our approach: We remove duplicate entries of bonds with matching 9-digit CUSIP, 6-digit CUSIP, offering date, and maturity date.

4. Bond Reopenings: Some issuers opt to reopen an existing bond issuance, increasing the amount of the bond outstanding while keeping other characteristics unchanged, rather than issuing new bonds. In the SDC, these reopenings are recorded as new deals with distinct deal IDs.

Our approach: We identify reopenings by matching bonds with the same 9-digit CUSIP, same 6-digit CUSIP, and maturity date but different offering dates. We restrict our analysis to bonds where the number of unique observations matches the number of unique offering dates. For our dataset, which includes bond characteristics to be used to identify the financial innovations, we retain only one observation (the initial offering) per reopening group. However, for tracking amounts offered and offering spreads over time, we retain all observations within a reopening group.

5. Multiple Observations per 9-digit CUSIP: Some transactions are recorded multiple times under the same 9-digit CUSIP, but these observations are neither reopenings nor maturity extensions. Such cases are typically seen with financial institutions (securitizers) and federal agencies.
   Our approach: We remove bonds with multiple entries under the same 9-digit CUSIP that are not identified as reopenings.

6. Other Duplicates: Some deals in the SDC Platinum lack 9-digit CUSIP.
   Our approach: We identify duplicates among such bonds based on the 6-digit CUSIP, offering date, maturity date, and coupon characteristics (coupon rate for fixed-coupon bonds, and floating rate index plus basis point spread for floating rate bonds).

C.2 SDC Platinum: Defining a financial product

The classification of financial products is based on a detailed examination of contractual characteristics recorded in the SDC Platinum database. We use structured issuance data from 1970 to 2020, covering a broad set of transactions in the U.S. capital market. A comprehensive set of product features—relevant to investor rights, payment structures, and structural provisions—is extracted and converted into binary (dummy) variables, indicating the presence (1) or absence (0) of each characteristic. This allows each security to be represented as a vector of zeros and ones, where the position of each element corresponds to a specific feature. This standardized representation facilitates consistent product identification and enables empirical analysis across a large sample.

Below is a list of all characteristics from SDC Platinum used in the identification process:

1. Periodic Payment Characteristics (Coupon for debt instruments and dividend for equity instruments):

- Level 1 Type: Fixed Rate, Floating Rate, Equity-Related, Not Applicable.
- Level 2 Type: Annuity, Fixed Rate, Floating Rate, Indexed, Reset, Serial, Varies, Zero.
- Payment Reference Asset: Captures the asset or benchmark to which periodic payments are linked. Examples include gold, silver, the federal funds rate, various currencies, and U.S. Treasury bills. A total of 76 distinct reference assets are included. "NA" indicates missing information.
- Dual Coupon Flag: Indicates whether the instrument switches between fixed and floating rate payments over its term.
- Periodic Step Flag: Indicates whether the payment amount steps up or down at specific intervals.
- Mismatched Coupon Payment Flag: Indicates that the frequency of interest payments differs from the coupon reset frequency.
- Inverse Link Flag: Payment is inversely linked to the reference asset.
- Credit Sensitive Flag: Coupon payment depends on the issuer's credit rating.
- Capital Coupon Flag: Interest is paid in the form of additional debt.
- Pay-In-Kind Coupon Flag: Interest is paid in-kind rather than in cash.
- Dividend Payment Type: Fixed Rate, Reset Auction or Remarketed Rate, Variable Rate.
- Cumulative Dividends Flag: Dividends are cumulative.

2. Maturity Characteristics:

    - Maturity Type: Amortization, Bullet Maturity, Extendible Maturity, Maturity Linked to Index, Perpetual Maturity, Scheduled Early Redemption.
    - Perpetual Maturity Flag: No sinking fund or mandatory conversion.
    - Maturity Ineligible Flag: Transaction maturity is less than 360 days.

3. Issuer Legal Structure:

    - REMIC Flag: Real Estate Mortgage Investment Conduit.
    - Limited Partnership Flag: Issuer is a limited partnership.
    - Fund/Trust Flag: Issuer is a fund or trust.

- Closed-End Fund/Trust Flag: Issuer is a closed-end investment fund or trust with a fixed number of shares that are not redeemable.
- LLC Flag: Issuer is a tax-haven limited liability company.
- Unit Investment Trust Flag: A registered trust with a fixed portfolio of income-producing securities held to maturity.

4. Equity Characteristics:

   - Depositary Issue Flag: Shares offered represent a fraction of a share.
   - Voting Rights Type: Limited voting, non-voting, voting, or unspecified.
   - Unit Issue Flag: Combination of securities such as stock and warrants.
   - Covenant Type: Indicates protective features such as limitations on debt, pari passu provisions, or cross-default clauses. 11 covenant types are tracked.

5. Collateral Attributes:

   - Asset-Backed Security Flag: Indicates mortgage or asset-backed securities.
   - Asset-Backed Type: Includes pass-through certificates.
   - Type of Collateral: Specifies underlying assets such as leases, receivables, or credit default swaps. Total of 73 types.

6. Conversion and Exchange Characteristics:

   - Convertible Issue Flag: Securities can be converted into common stock.
   - Variable Conversion Flag: Conversion price is not fixed.
   - Conversion Ratio Limits: Restrictions on number of shares upon conversion.
   - Mandatory Conversion Flag: Conversion into common stock is mandatory.
   - Contingent Conversion Trigger Type: Conversion conditional on stock price thresholds (upward or downward).
   - Exchangeable Flag: Securities exchangeable for shares of another company or other assets.
   - Type of Exchangeable Asset: Includes cash, debt, gold, and equity. Ten types in total.

7. Embedded Option Characteristics:

    - Equity Call Flag: Redemption proceeds tied to a future equity offering.
    - Net Worth Call Flag: Issuer repurchase required if net worth drops below a threshold.
    - Put Type: Includes extendible, limited, poison, or standard puts.
    - Call Protection Type: Includes make-whole calls, equity calls, non-callable structures, etc. Total of 10 types.
    - Callable/Puttable Within One Year Flag: Instrument is callable or puttable within one year.

8. Miscellaneous Characteristics:

    - Capital Security Type: Additional Tier 1, Lower Tier 2, Tier 1, Tier 2, Upper Tier 2.
    - Equity-Related Flag: Includes equity-linked instruments.
    - Hybrid Security Flag: Combines debt and equity features.
    - Currency of Issue: Denomination currency. Total of 66 currencies.

To illustrate the identification process, Table (C.1) presents examples of some of the most popular financial products, highlighting the characteristics that are non-zero (i.e., those present in the product's vector).

Table C.1: Examples of Financial Products and Characteristics

Financial Product, Broad Type	Characteristics	Year	Number of Issues
Debt	Fixed Rate, Payment Reference Asset==”NA”, Bullet Maturity, Voting Rights ==”NA” Currency==”US Dollar”, Non-Callable to Maturity	1970	65,104
Debt	Fixed Rate, Payment Reference Asset==”NA”, Scheduled Early Redemption, Voting Rights ==”NA” Currency==”US Dollar” Non-Callable until specified date	2003	32,331
Debt	Fixed Rate, Payment Reference Asset==”NA”, Maturity type==”NA”, Voting Rights ==”NA” Currency==”US Dollar” Non-Callable until specified date	1971	29,638
Debt	Fixed Rate, Payment Reference Asset==”NA”, Maturity type==”NA”,Voting Rights ==”NA”, Currency==”US Dollar”,Non-Callable to Maturity	1980	25,783
Debt	Fixed Rate, Payment Reference Asset==”NA”, Scheduled Early Redemption, Voting Rights ==”NA”, Currency==”US Dollar”, Non-Callable until specified date Callable/Puttable Within One Year	1986	25,621
Debt	Fixed Rate, Payment Reference Asset==”NA”, Maturity type==”NA”, Voting Rights ==”NA”, Currency==”US Dollar”, Non-Callable until specified date Callable/Puttable Within One Year	1979	25,235
Common Stock	Coupon Not Applicable, Payment Reference Asset==”NA”, Maturity type==”NA”, Voting Rights ==”NA”, Currency==”US Dollar”,Equity Related	1970	22,166
Asset-Backed Security	Fixed Rate, Payment Reference Asset==”NA”, Bullet Maturity, Voting Rights ==”NA”, Currency==”US Dollar”,Non-Callable to Maturity, REMIC, Asset-Backed Pass Through Certificate, Collateral type==”Mortgage Loan”	1987	19,215
Common Stock	Coupon Not Applicable, Payment Reference Asset==”NA”, Maturity type==”NA”, Voting Rights==”Voting Rights”, Currency==”US Dollar”, Equity Related	1971	16,893
Asset-Backed Security	Fixed Rate, Payment Reference Asset==”NA”, Bullet Maturity, Voting Rights ==”NA”, Currency==”US Dollar”,Clean Up Call, REMIC,Asset-Backed Pass Through Certificate, Collateral type==”Government Loans”	1988	13,943

Table (C.1) shows that the most common financial instruments are minor variations of fixed-rate bonds, common stock, and asset-backed pass-through certificates. This demonstrates that our definition of products captures fine distinctions due to the granularity of the characteristic set.

C.3 Matching procedure for SDC Platinum New Issues and Capital IQ Compustat databases

We match SDC to Compustat as follows:

1. Match by firms' 6-digit CUSIP reported in SDC and Compustat.
2. Match by firms' 6-digit CUSIP reported in SDC and CRSP, extend to Compustat using CRSP-Compustat link.
3. Match CUSIP 6-digit reported in other issuances with same alternative identifiers (issuer name, CIK code, SDC issuer code, etc.) that has already been linked to Compustat in the first step.
4. Repeat steps 1-3 using firms' Ultimate parent 6-digit CUSIP.

C.4 Compustat: Data Construction

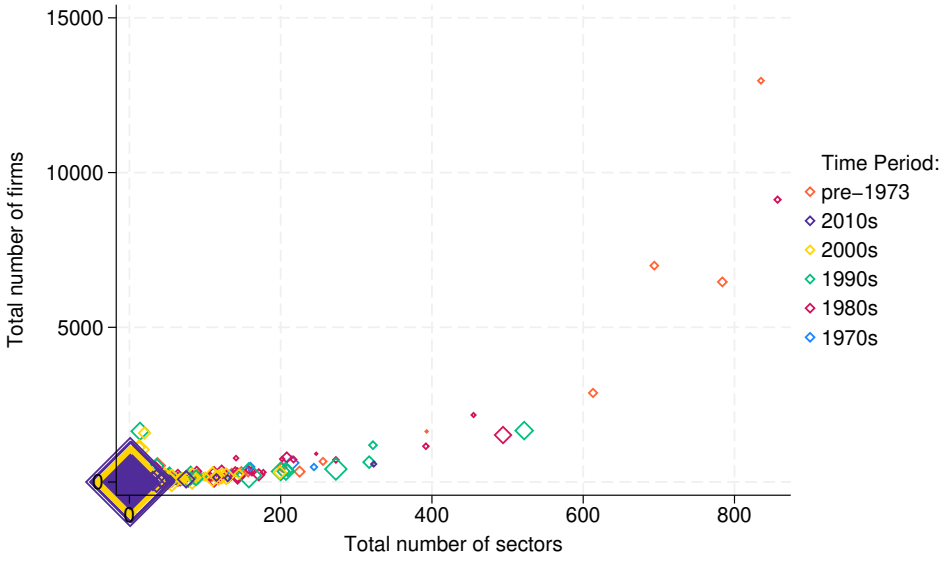
This appendix provides details on the firm financial variables used in the empirical analysis, based on quarterly Compustat data. The definition of the variables follows that in ottonello2020financial.

Variables:

1. Size: the log of total real assets (at), deflated using the BLS implicit price deflator.
2. Real sales: sales (sale) deflated using the BLS implicit price deflator.
3. Real sales growth: log differences in real sales.
4. Employment: number of employees (emp).
5. Age: defined as the minimum of the following measures: the number of years since CRSP listing, the number of years since IPO and year of incorporation as reported in ritter2021initial, and the year of incorporation from Datastream.
6. Leverage: the ratio of total debt (sum of dlc and dltt) to total assets (at).

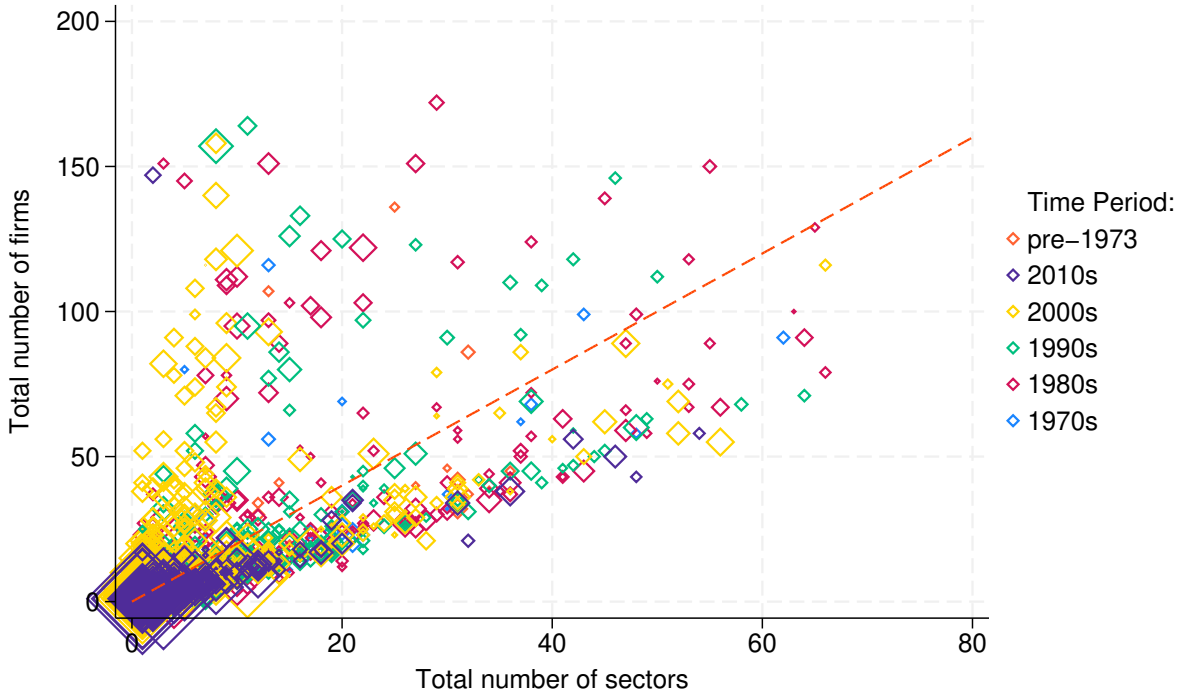
C.5 Diffudion of Financial products

Figure C.1: Sectoral and Firm-Level Diffusion of Financial Instruments, 1970–2020



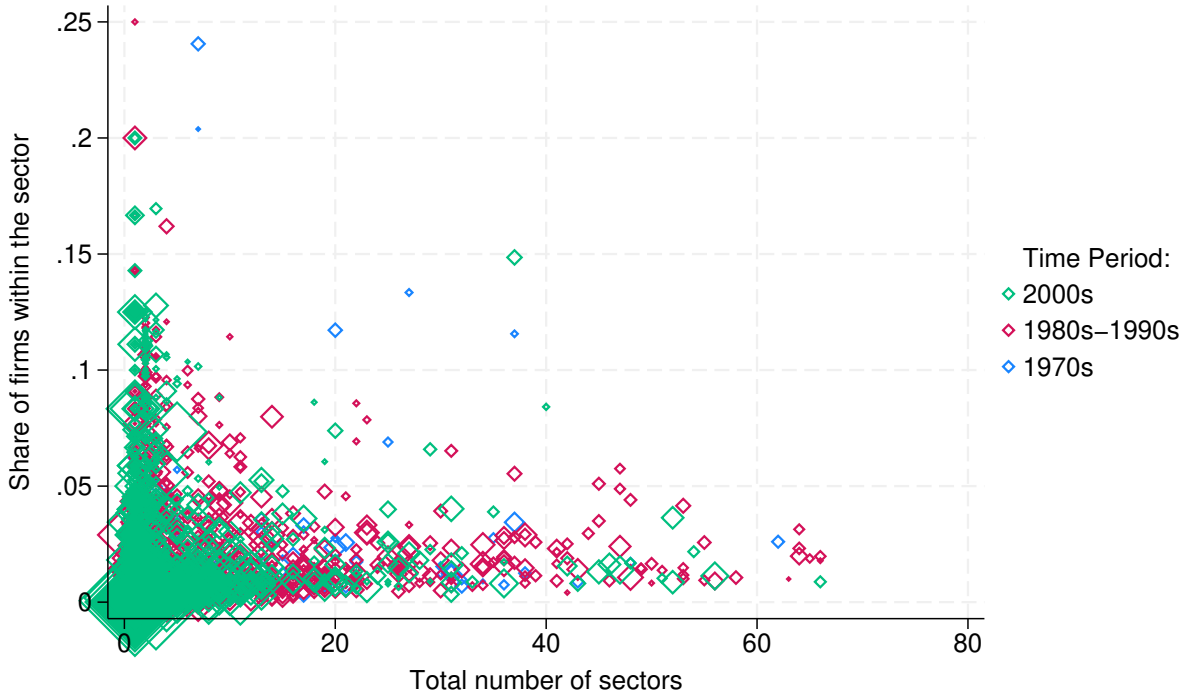
Notes: The figure shows how financial instruments have evolved over 1970-2020. The scatter plot visualizes the relationship between the total number of firms that have ever issued a given financial instrument and the total number of sectors in which the instrument has been issued. Each diamond represents a financial instrument, with its size reflecting the relative mean principal amount per issuance. The color of the diamond indicates the decade in which the instrument was first introduced.

Figure C.2: Bottom 99% Most Widely Adopted Financial Instruments by Firms and Sectors



Notes: This figure illustrates the evolution of financial instruments from 1970 to 2020. The scatter plot visualizes the relationship between the total number of firms that have ever issued a given financial instrument and the total number of sectors in which the instrument has been issued. Each diamond represents a financial instrument, with its size reflecting the relative mean principal amount per issuance, while its color indicates the decade of first introduction. The plot displays a sample of financial instruments where the total number of firms and sectors fall within the 99th percentile. The 60-degree reference line indicates that, for points above the line, at least two firms in each sector have issued the instrument.

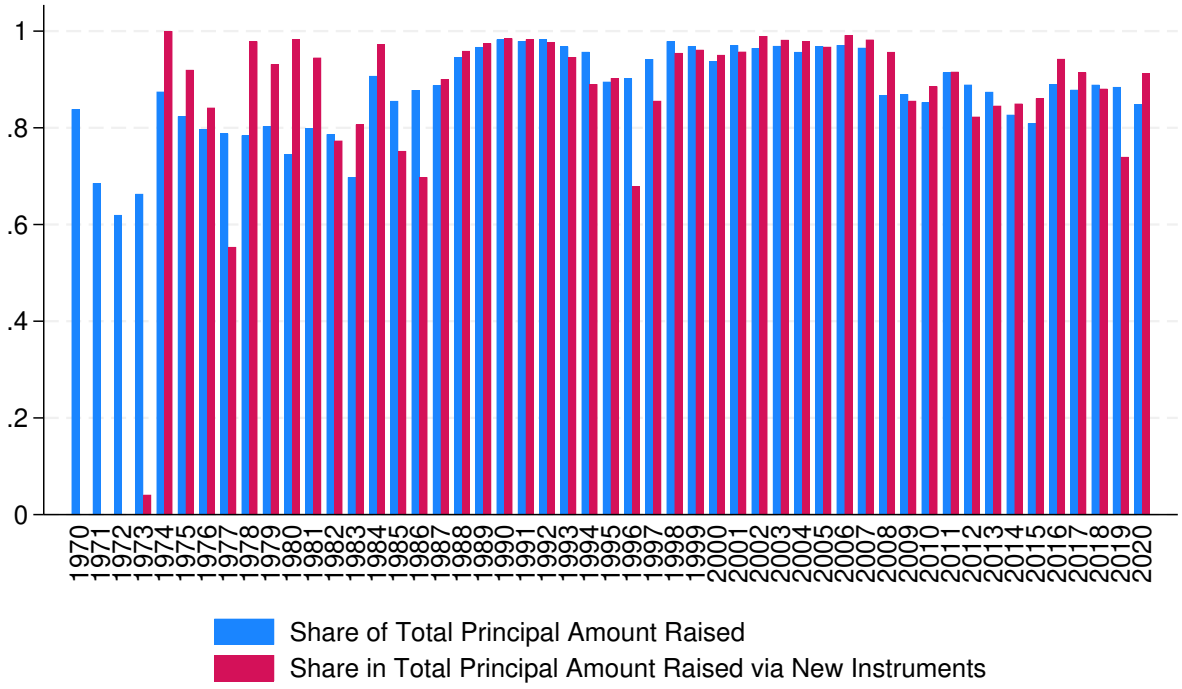
Figure C.3: Within-Sector Firm Adoption of Widely Issued Financial Instruments (99th Percentile)



Notes: This figure illustrates the evolution of financial instruments from 1970 to 2020. The scatter plot visualizes the relationship between the average share of firms issuing a given financial instrument across sectors and the total number of sectors in which the instrument has been issued. Each diamond represents a financial instrument, with its size reflecting the relative mean principal amount per issuance, while its color indicates the decade of first introduction. The plot includes only instruments where more than one firm has issued the instrument within a sector, and the total number of sectors falls within the 99th percentile.

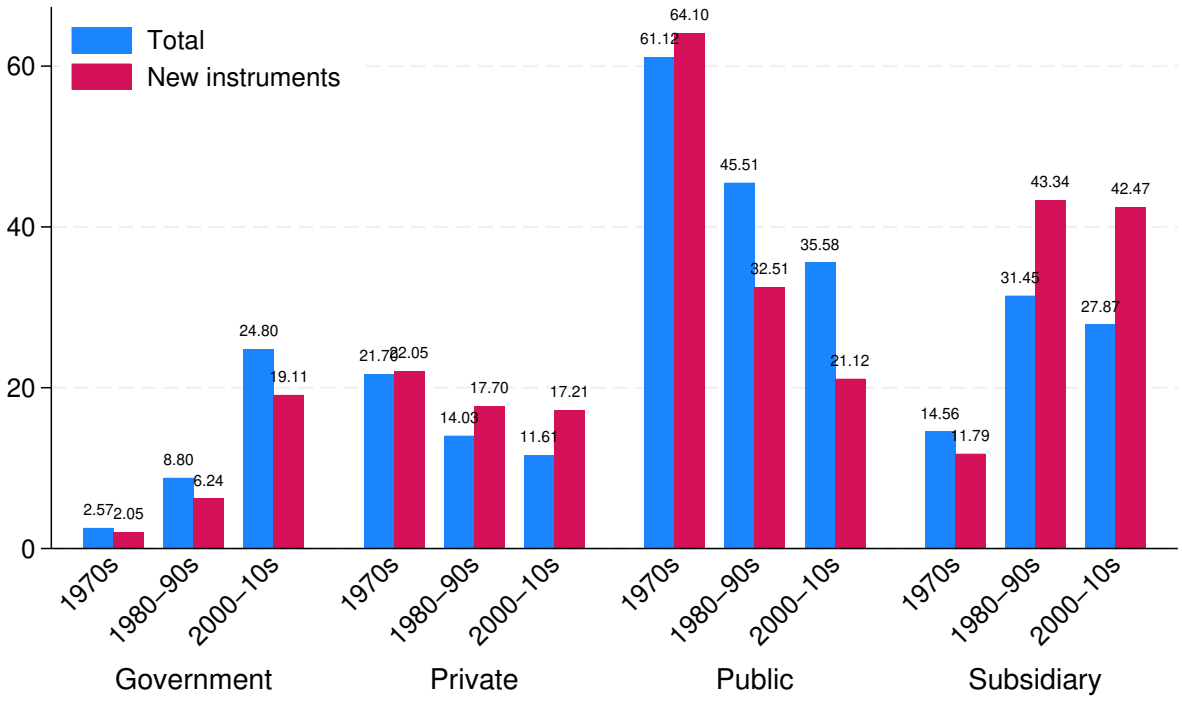
C.6 Additional facts

Figure C.4: Share raised via debt instruments



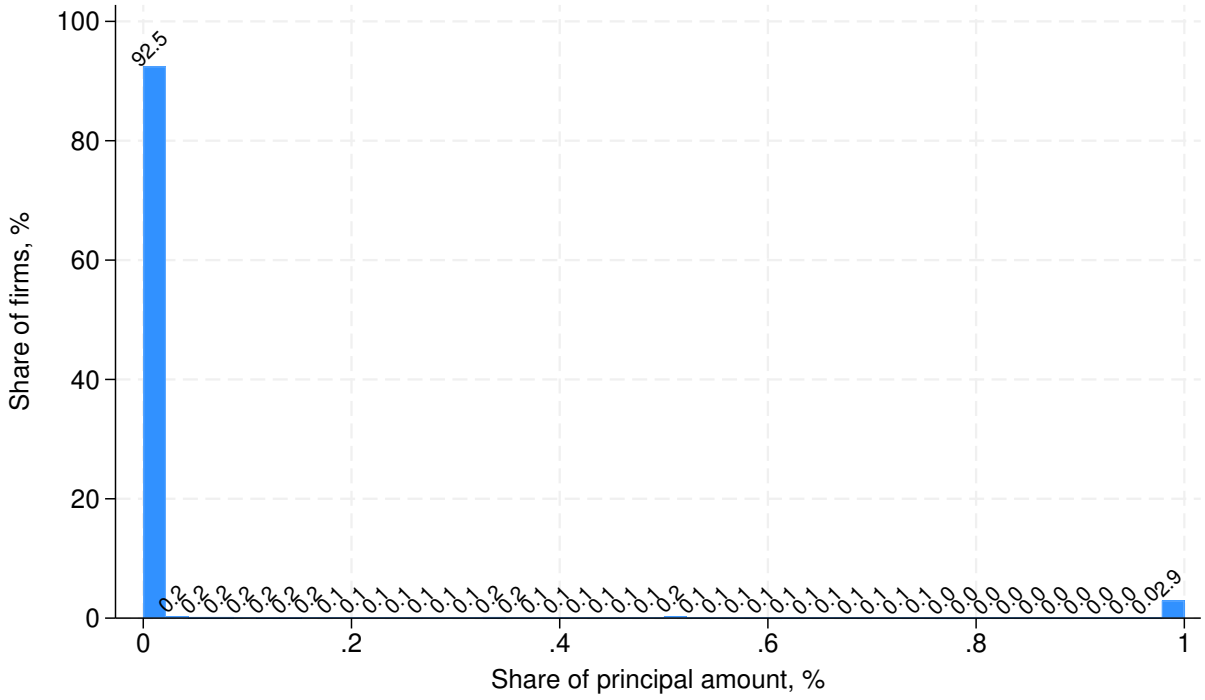
Notes: This graph displays the share of capital raised through debt instruments introduced each year from 1973 to 2020. For each year, the two bars represent (1) the share of debt instruments in total issuance by principal amount and (2) the share of newly introduced debt instruments in total newly introduced financial instruments. A financial instrument is considered new for 365 days after its first transaction. The horizontal axis represents the year of introduction.

Figure C.5: Incidence by the type of issuer



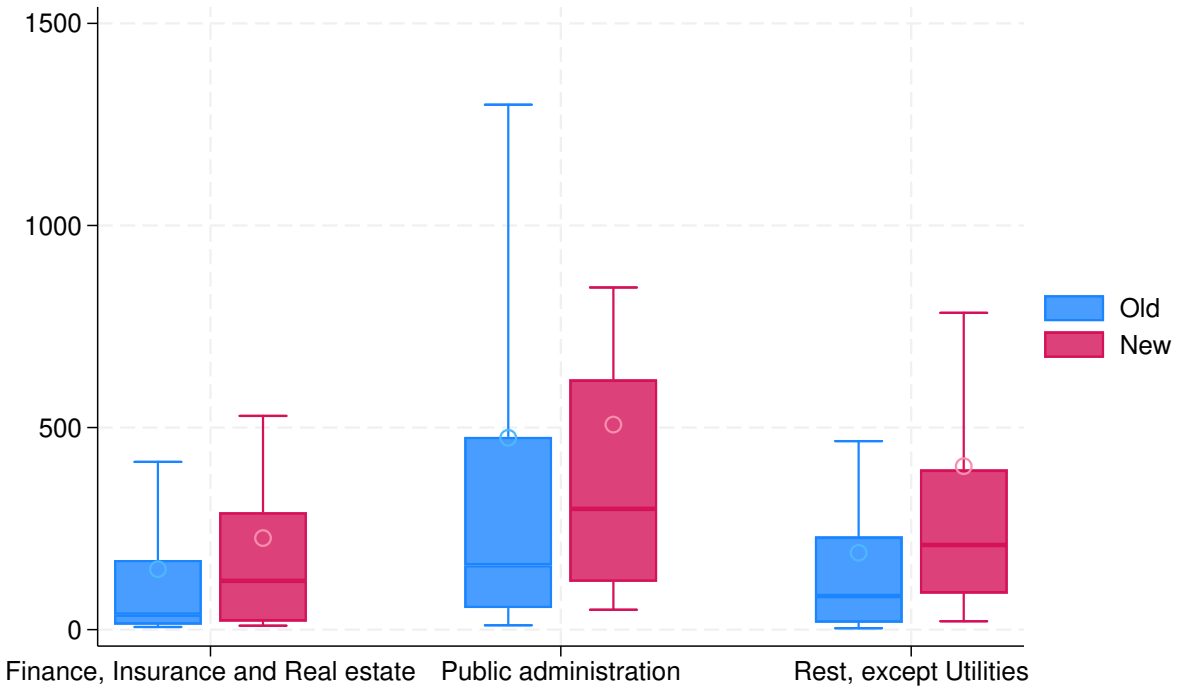
Notes: This graph shows the percentage of the transactions in both the total market and the market for newly issued instruments, categorized by issuer public status, over sample subperiods from 1970 to 2020. A financial instrument is considered new for 365 days after its first transaction. The horizontal axis represents the year of introduction.

Figure C.6: Distribution of Novel Instrument Usage by Share of Principal Issued



Notes: This histogram illustrates the distribution of firm-year observations based on the share of total principal amount issued using novel financial instruments. The x-axis represents the proportion of total funds raised in a given year that came from novel instruments, ranging from 0 (no principal raised through novel instruments) to 1 (entire principal raised through novel instruments). The y-axis reflects the frequency of firm-year observations corresponding to each share interval.

Figure C.7: Distribution of Proceeds per Issuance by Issuer Sector



Notes: The figure shows the distribution of proceeds per issuance (in millions of US$, real) at the transaction level, with statistics provided for broad issuer sectors and for both new and old products. The Finance, Insurance, and Real Estate sector includes 2-digit SIC industry codes between 60 and 67, the Public Administration sector includes codes between 91 and 97, and the Rest of the Economy excludes utility code 49. A financial instrument is considered new for 365 days after its first transaction. For each instrument type, we plot five sample statistics: the 10th percentile, lower quartile, median, upper quartile, and 90th percentile, with the dot representing the average proceeds.

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