Upwardly Mobile: The Response of Young vs. Old Firms to Monetary Policy*

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Abstract

We study heterogeneity in the response of firm investment to monetary policy. We estimate firm-specific semi-elasticities to plausibly exogenous changes in interest rates in a comprehensive data set that covers ten euro area countries. Using a machine learning algorithm, we find that firm age best predicts differences in these semi-elasticities across firms. Impulse response functions show that investments of young firms are significantly more sensitive to monetary policy than investments of older firms. We rationalize this finding in a lifecycle firm model with convex and fixed capital adjustment costs. Older firms are less responsive to shocks because they are closer to their optimal scale, and thus less likely to pay the fixed cost. One key implication is that monetary policy is less potent in an economy with older firms.

Keywords: Firm heterogeneity, Monetary policy transmission, High-frequency identification, Random Forest, Capital adjustment costs

JEL Classification: D24, E22, E44, E52

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1 Introduction

The reaction of firms to changes in the interest rate is an important channel for monetary policy transmission. In this paper, we study heterogeneity in the response of investment across firms. This is useful for understanding the macroeconomic propagation mechanism of monetary policy, as well as the distributional implications. Moreover, we use monetary policy shocks as a laboratory for learning about firm investment more generally.

We take an agnostic approach to detect which firm characteristics predict differences in firm investment responses to monetary policy. The analysis uses the comprehensive firm-level Orbis database by Bureau van Dijk, which covers a large number of non-financial firms for ten euro area countries. For each firm, we estimate a firm-specific semi-elasticity of physical capital to identified monetary policy shocks. For identification, we rely on high-frequency surprises in interest rates around meetings of the European Central Bank's Governing Council.[1] We then implement a Random Forest algorithm (Breiman, 2001) to find which variable best explains variation in the estimated semi-elasticities.

Firm age is the most important variable for explaining heterogeneity in investment responses to monetary policy shocks across firms. It is a better predictor of a firm's capital semi-elasticity than other variables by a wide margin, including firm size and financial variables such as leverage and a cashflow-based measure. The result holds across time periods, and whether or not we include the effects of firm entry and exit.

To quantify the relationship between a firm's age and its capital semi-elasticity, we group firms by age and estimate a single semi-elasticity for each group. Younger firms' investments are more sensitive to changes in monetary policy than older firms' investments. The responsiveness declines gradually in age, and is statistically insignificant for older firms. Specifically, three years after a contractionary monetary policy shock (an interest rate increase) of 25 basis points, the total fixed assets of firms between 0 and 5 years old are seven percent lower than they would be absent the shock, whereas the total fixed assets of firms around 40 years old are only one percent lower. It follows that firms between 0 and 5 years old are responsible for 35% of the aggregate capital stock response to monetary policy shocks, even though they hold only 11% of the capital stock. Finally, although we focus on firms' capital stocks, we show that our main results hold for employment as well.

We demonstrate that a lifecycle firm model with capital adjustment costs can rationalize

[1] This identification strategy goes back to Kuttner (2001), and is used widely in the recent literature on the effects of monetary policy.

our findings. Firm production is decreasing returns to scale in capital, the only input. Firms enter with a low initial level of capital, which they expand over time subject to a fixed and a convex adjustment cost. As a firm ages, it approaches its optimal size, and its likelihood of paying the fixed cost falls.

The key outcome of the model is that younger firms are more likely to respond to an unanticipated interest rate shock. The interest rate determines the user cost of capital, and so a firm's optimal size. A young firm responds to a change in the user cost because it is far from its optimal size, so it pays its fixed cost with or without the shock. On the other hand, an old firm does not respond to a sufficiently small shock because it is close to its optimal size, and so not willing to pay the fixed cost.

The model explains the higher responsiveness of young firms in our local projections, as well as the finding of our Random Forest algorithm that age is the best predictor of a firm's response. Our theory is that a firm's age is a proxy for its distance to its optimal scale, which determines its willingness to pay fixed adjustment costs, and is not picked up by other variables in the data. For example, if a young firm is large, then it must have an even larger optimal size, and so is still paying its fixed adjustment cost.

We focus on a simple model of a single firm to illustrate the theory. Nonetheless, it makes sharp qualitative predictions that we find evidence for in the data. In the theory, older firms invest less as a share of their capital stocks, and as a result, they are less likely to change their capital stocks at all. In the data, the average percentage change in a firm's stock of fixed assets is decreasing with age. This holds unconditionally, as well as if we control for firm size and firm fixed effects. Furthermore, older firms bunch a larger share of their capital growth close to zero.

The findings have several implications for the effects of monetary policy. First, the aggregate investment response to interest rate shocks masks the effects on different groups of firms. Although a small number of large older firms are responsible for much of aggregate investment, they are less sensitive to monetary policy. Thus, the size of the aggregate investment response is not representative of the effects on the majority of firms. Second, changes in the firm age distribution imply changes in the aggregate effects of interest rate shocks. For example, the theory suggests that the fall in firm entry and shift toward older firms over the past few decades reduced the potency of monetary policy. Similarly, different firm age distributions across countries can generate different aggregate responses to monetary policy. In particular, in the euro area, where there is one central bank presiding over several countries, this implies a stronger transmission to countries with a larger share of young firms.

Finally, our results suggest that a firm's age is an important determinant of its responsiveness to shocks more generally. A firm's size and financial position may appear to predict how it will react to changes in its environment, but may simply be correlates of firm age, reminiscent of the finding in Haltiwanger et al. (2013) that a firm's size does not predict its growth rate when controlling for age. This is particularly important as the relationship between other variables and firm age changes over time or across economies.

Related literature. This paper contributes to the literature on heterogeneity across firms in the transmission of monetary policy. In previous work, various dimensions are significant predictors of a firm's response, including age (Durante et al., 2022, Cloyne et al., 2022), size (Gertler and Gilchrist, 1994, Crouzet and Mehrotra, 2020), bank dependence (Crouzet, 2021, Holm-Hadulla and Thürwächter, 2021), and balance sheet characteristics such as leverage and liquidity (Ottonello and Winberry, 2020, Jeenas, 2019, Auer et al., 2021). Relative to these papers, we take an agnostic approach to identify the most important variable for investment response heterogeneity across firms. The data we use include a broad set of firms, and so are well-suited for this approach.[2]

We also add to the related literature on the theory of how monetary policy affects firms, and why the effects differ across firms. Previous work primarily relies on financial frictions for explaining monetary policy transmission (Bernanke and Gertler, 1995) and heterogeneity in transmission across firms (Ippolito et al., 2018, Jeenas, 2019, Ottonello and Winberry, 2020, Durante et al., 2022, Jungherr et al., 2022). By contrast, we propose a mechanism that relies only on real frictions in the form of capital adjustment costs. As in Khan and Thomas (2008), Winberry (2021), and Koby and Wolf (2020), heterogeneity across firms in their responses to aggregate shocks follows from heterogeneity in the proximity of firms' capital stocks to their optimal levels. We link this mechanism to firm age, and argue that younger firms' capital stocks are further from their optimal levels.

Finally, our findings contribute to the literature on capital adjustment costs and investment dynamics. Early papers by Caballero and Engel (1999) and Cooper and Haltiwanger (2006) find that fixed costs help match the lumpiness of investments in firm microdata. We provide indirect evidence for fixed costs by showing they can explain a higher responsiveness to monetary policy shocks among younger firms. In particular, we demonstrate that they provide a better explanation than financial frictions. This suggests that a firm's age is a po-

[2] With the exception of Crouzet and Mehrotra (2020) and Durante et al. (2022), the above cited papers that use microdata rely on U.S. Compustat firms. These firms tend to be relatively large and thus constitute a narrow subset of the firm distribution.

tential proxy for whether it is constrained by fixed adjustment costs. Moreover, the effects of fixed adjustment costs are more likely to apply to older firms.

Outline. In Section 2, we describe the underlying firm-level data. We discuss the identification of monetary policy shocks and lay out the empirical framework used in the analysis in Section 3. In Section 4, we present our main empirical results on the importance of firm age for how firms respond to monetary policy. In Section 5, we present a dynamic investment model that rationalizes our empirical findings, provide empirical evidence for the model's main predictions, and evidence against other potential models. We conclude in Section 6.

2 Firm-level data

2.1 Overview

We use panel data on private and public firms from the Orbis database by Bureau van Dijk. Our sample consists of 7.7 million non-financial firms for ten euro area countries over the time period 1999 to 2018.[3] The starting point coincides with the inception of the euro area. We obtained the data from the recently launched Orbis Historical database, which contains the time series for each firm going as far back in time as possible. This overcomes the previous limitation that Orbis data were only available for a fixed amount of years. The data include annual observations on each firm's balance sheet and income statement as well as sector, age, number of employees, and other characteristics. To clean the data, we closely follow the detailed guidance by Kalemli-Özcan et al. (2019), as well as additional steps outlined by Durante et al. (2022). Last, we perform manual data checks for all variables.

Although firms report only once in a given calendar year, there is variation in the month of reporting across firms. To keep the largest possible variation along the time series dimension, we take into account the month and year of each observation. We exclude observations where firms vary the month of reporting over time so that the time between reports for any given

[3] The countries are Austria, Belgium, Germany, Greece, Spain, France, Finland, Italy, the Netherlands and Portugal. Combined, they account for more than 95% of total euro area GDP. All countries have been members of the monetary union since 1999 except for Greece, which joined the euro area in 2001. In terms of sectors, we exclude the following NACE groups: Agriculture, Forestry, Fishing (A), Financial and insurance activities (K), Real estate activities (L), Public administration and defence, and Compulsory social security (O), Education (P), Activities of households as employees (T), Activities of extraterritorial organizations and bodies (U). Further sample restrictions are to exclude firms with activity status "Inactive", "Unknown" and "Active (dormant)" as well as firms with missing information for the date of incorporation.

firm is always twelve months.[4] All nominal variables are deflated with the monthly HICP (Harmonized Index of Consumer Prices) from the country where the firm filed its report. To avoid distortions due to outliers, we winsorize all variables, including growth rates and other transformations, at the 1% and 99% levels. Appendix A.1 contains a list of all variables and transformations for the data used in the main part of the paper.

2.2 Sample description

In each country, the sample has good coverage of the aggregate economy: gross output within the sample are more than 60% of aggregate sales for most countries, and as high as 80% for some countries (see Table A.2 in Appendix A.2).[5] Moreover, in each country, the sample firm size distribution is close to the overall firm size distribution (see Figure A.1 in Appendix A.2 for details).

Table 1: Summary statistics for firm-level data.

	N	Mean	p10	p50	p90	Max
Total assets (m€)	60,135,508	4.99	0.03	0.30	3.27	245,847.83
Gross sales (m€)	42,308,856	4.95	0.02	0.34	4.17	149,706.80
Number of employees	32,159,393	20.83	1	4	30	323,298
Firm age	60,135,508	13.32	1	10	29	901

Note: Total assets and gross sales are in millions of euros, and are deflated using the HICP index of the respective country with base year 2015. The number of employees is the number of persons employed. Firm age is in years, and is the difference between the year of reporting and the year of incorporation. p10, p50, and p90 are the 10th, 50th, and 90th percentiles.

Table 1 shows selected summary statistics. We highlight two features of our comprehensive sample. First, the number of observations is large. Balance sheet information, for example total assets, are available for more than sixty million firm-year observations. The number of employees and income statement information, such as gross sales, are reported less frequently, but are available for more than half the observations. Importantly, the date of incorporation that we use to compute firm age is widely available. Second, the distribution of firms is wide. There are a few large and old firms (one firm is more than 900 years old[6]),

[4] If a firm features different reporting months within the sample, we maintain the observations from the month with the largest number of observations. If there are multiple months with the same number of observations, we choose one randomly.

[5] For this comparison, we adjust our selection of sectors to match those underlying the OECD data. Appendix A.2 provides further details.

[6] This is a German brewery, based in Bavaria, operating in the tradition of an old monastery.

but the majority are young and small. This reflects that most firms in Orbis are privately held, so our sample is representative of the broad distribution of firms in the economy.

3 Empirical framework

We now discuss the identification of exogenous monetary policy shocks, and estimate their average effect on firms' capital stocks at different time horizons. We turn to the heterogeneity of firms' responses in Section 4.

3.1 Identification of monetary policy shocks

We use high-frequency surprises in short-term interest rates around Governing Council meetings of the European Central Bank (ECB) to identify monetary policy shocks.[7] The identifying assumption is that a change in the interest rate over a narrow window around a meeting is solely attributable to the decisions of the central bank, and does not reflect other changes in aggregate conditions. We obtain intraday surprises for the meetings of the ECB Governing Council from the Euro Area Monetary Policy Event-Study Database, provided by Altavilla et al. (2019).[8] We use the change in the 3-month OIS rate from before the press release to after the press conference.

Following Jarocinski and Karadi (2020), we restrict attention to shocks in which the interest rate and stock prices move in opposite directions. The idea is to focus on the effects of a change in the interest rate, rather than the effects of a change in information caused by the central bank's actions. An increase in the interest rate, on its own, should lower stock prices because it raises the discount rate on future dividends, and reduces future dividends (by lowering output). However, people may infer from a contractionary monetary policy shock that the central bank has positive private information about the state of the economy. If this second channel dominates, then stock prices rise.[9] Figure 1 plots all surprises in the 3-month OIS rate and the concurrent changes in the stock market index. We only use shocks located in the second and fourth quadrants, marked with a diamond.

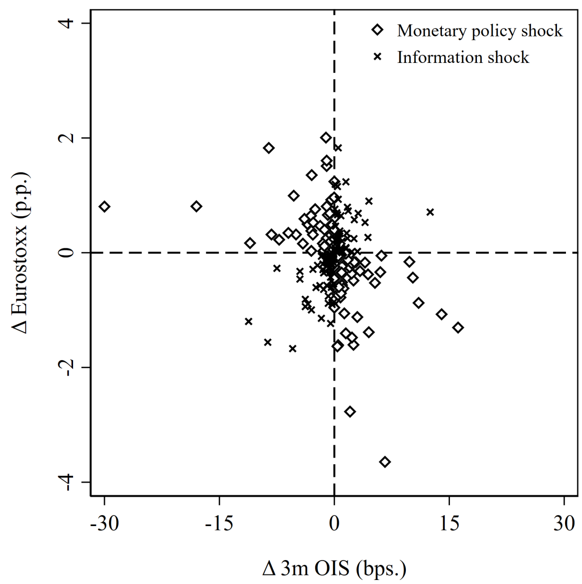
To examine the plausibility of our identified monetary policy shocks, we estimate impulse

[7] See Kuttner (2001), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Altavilla et al. (2019), and Ramey (2016) for discussions of this approach.

[8] The database is updated regularly and can be downloaded at `https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx`.

[9] Andrade and Ferroni (2021) and Nakamura and Steinsson (2018) also discuss the distinction between these two types of effects for the euro area and the US, respectively.

Figure 1. Stock price and policy rate surprises.



Note: The figure shows high-frequency changes in the 3-month OIS rate and the Eurostoxx index around all meetings of the ECB Governing Council between 1999 and 2018. Surprises marked with a diamond (second and fourth quadrants) are classified as monetary policy shocks, and surprises marked with a cross (first and third quadrants) are classified as information shocks. The data are from the Euro Area Monetary Policy Event-Study Database by Altavilla et al. (2019).

response functions for various aggregate variables following an identified shock. Figure B.2 in Appendix B.2 displays the results for the short-term euro area interest rate, GDP, total domestic investment, and the GDP deflator, which are in line with previous estimates in the literature. In particular, following a contractionary shock, the short-term rate jumps and then briefly increases further before reverting back to its pre-shock value. GDP and investment decline with a lag and reach a trough after about two years. Prices fall with a lag and only begin to revert back after about three years.

Finally, to match the shocks with our firm-level data, we compute their twelve-month moving sum. Firms reporting in a given month are then linked to the sum of all monetary policy surprises in the previous twelve months. Figure B.1 in Appendix B.1 shows the time series of the shock and its twelve-month moving sum.

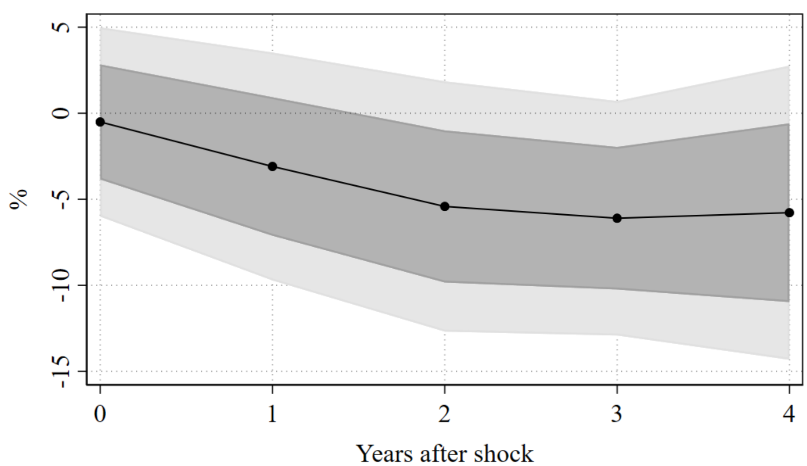
3.2 Homogeneous effects of monetary policy shocks

We use the local projections method developed by Jordà (2005) to estimate impulse response functions for firms' log capital stocks following identified monetary policy shocks. We begin with a baseline specification in which the response is the same across firms:

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \beta_h shock_t^{MP} + \Gamma_h' X_{t-1} + \epsilon_{i,t+h}, \tag{1}$$

where $h \in \{0, 1, \ldots, 4\}$ is the projection horizon (in years). The time t denotes a month and a year because firms report in different months. The outcome variable is the cumulative change in the log of firm i's tangible capital stock from a year before the shock, $t-1$, to h years after the shock, $t+h$: $\Delta_h Y_{i,t+h} \equiv \ln(\mathrm{k}_{i,t+h}) - \ln(\mathrm{k}_{i,t-1})$. On the right-hand side, $\alpha_{i,h}$ is a firm fixed effect, $shock_t^{MP}$ is the annualized identified monetary policy shock with coefficient β_h, X_{t-1} is lagged macroeconomic controls (year-on-year growth in industrial production and the price index at the country level) with coefficients Γ_h, and $\epsilon_{i,t+h}$ is the residual. Standard errors are two-way clustered at firm and time, where time is year-month. This takes into account potential serial correlation within a firm over time, as well as correlation across firms in a given month due to common influences.

Figure 2. Average investment response.



Note: The percentage response of firms' capital stocks to a 25 basis point contractionary monetary policy shock, implied by the semi-elasticities, $\{\hat{\beta}_h\}_{h=0}^4$, estimated from equation (1). The x-axis is the projection horizon, h. The light (dark) gray area is the 90% (68%) confidence interval, based on two-way clustered standard errors by firm and year-month.

The desired impulse response function is the path of the estimated semi-elasticity of firm capital with respect to the monetary policy shock at different horizons, $\{\hat{\beta}_h\}_{h=0}^4$. Figure 2 shows the implied response to a 25 basis point increase in the interest rate (a contractionary monetary policy shock). Firms' investments fall, and the cumulative effect on their capital stocks reaches a trough of -6.1% after three years, in line with the notion that monetary policy transmits to the real economy with a time lag. The estimates are statistically significant at the 68% level for a horizon of greater than or equal to 2 years. The magnitude of the decline is similar to previous estimates, such as Crouzet (2021) and Cloyne et al. (2022), who find a trough effect of -4.8% and -6.5%, respectively.

4 Heterogeneity in transmission

We now estimate the investment response to monetary policy shocks separately for each firm. We use a machine learning algorithm to detect which characteristics best explain differences across firms. Finally, we estimate group specific impulse response functions to quantify the effect of the most important characteristic, age, on firms' reactions to monetary policy. In Appendix G, we show that the results are similar if we use employment rather than capital as the outcome variable.

4.1 Firm-specific effects of monetary policy shocks

We estimate the following equation separately for each firm

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \beta_{i,h} shock_t^{MP} + \epsilon_{i,t+h}, \tag{2}$$

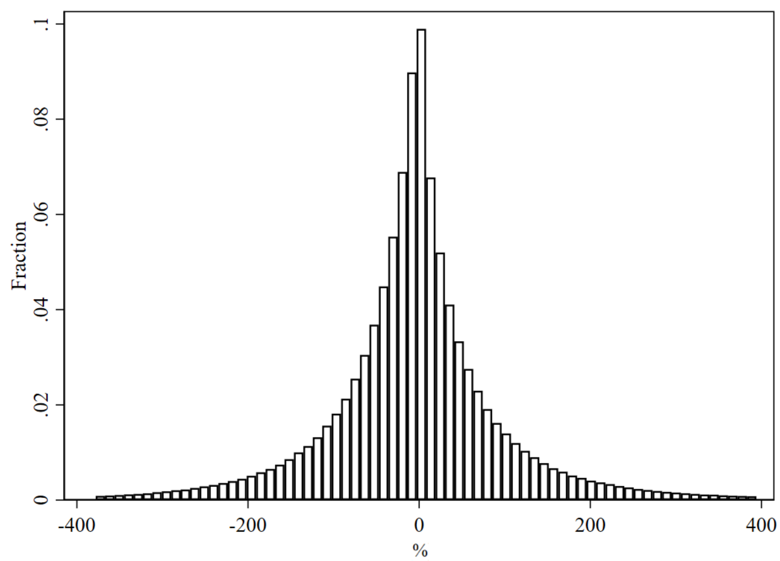
which is the same as the previous estimation equation (1)—the outcome variable is the change in the log of firm i's tangible capital stock from one year before the monetary policy shock, $t-1$, to h years after the shock, $t+h$—except the semi-elasticity with respect to the shock, $\beta_{i,h}$, is now firm-specific. Moreover, we leave out macroeconomic controls to keep as much variation within each firm as possible.[10]

We are interested in the estimated distribution of the semi-elasticities of firms' capital stocks with respect to the monetary policy shock, $\{\hat{\beta}_{i,3}\}$, where we focus on a horizon of $h = 3$ years after the shock to match the timing of the trough of the average response from Section 3.2. Figure 3 shows the implied distribution of responses to a 25 basis point

[10] We can estimate (2) for around 2 million of the 7.7 million firms in our sample. Since the outcome variable computes the difference in the log capital stock over several years, we can only keep firms with observations over at least five years.

increase in the interest rate. The unweighted mean is -4.8%, and the median is -4.1%. Many of the estimated responses are large, and even positive. This in part reflects general equilibrium forces: if a firm is not so responsive to the interest rate, then it may increase its capital following a monetary policy shock because its competitors decrease their capital. It also reflects that each estimate is relatively uncertain since it is obtained from a small set of observations for a single firm. If we restrict the sample to firms with a high number of observations, the dispersion in the estimated elasticities is more narrow. Hence, the distribution of firm-specific estimates should be interpreted with caution. In the following analysis, we also consider subsamples of elasticities, which are based on only firms with *(i)* a large number of observations and *(ii)* estimates that are statistically significant at the 10% level. Histograms of these subsamples are in Appendix C.

Figure 3. Histogram of firm-specific investment responses at $h = 3$.



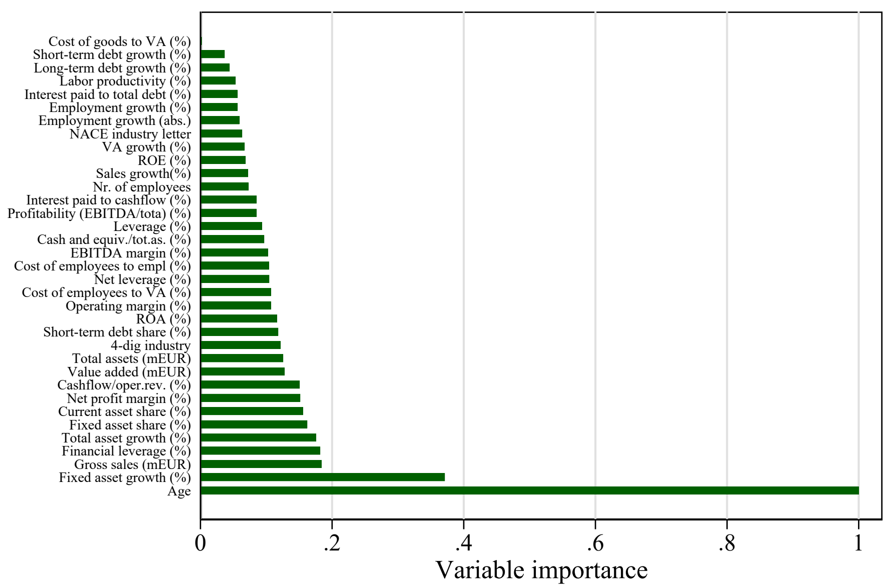
Note: The distribution of percentage responses of firms' capital stocks to a 25 basis point contractionary monetary policy shock, implied by the distribution of semi-elasticities, $\{\hat{\beta}_{i,3}\}$, estimated from equation (2) using a horizon of $h = 3$ years after the shock. The top and bottom 1% of the distribution are removed, and the number of bins is 70.

4.2 Detecting relevant firm characteristics

We now investigate which characteristics best predict firm-specific responses to monetary policy shocks, i.e., firms' $\hat{\beta}_{i,3}$. We use an agnostic approach: a Random Forest algorithm (Breiman, 2001). The algorithm identifies sample splits along observables that maximize variation in an outcome variable. This procedure has two key advantages. First, it allows for non-linear relationships between the outcome variable and explanatory variables, and among explanatory variables, which seems to be important when studying the transmission mechanism of monetary policy. Second, it does not suffer from the statistical issues that arise with multiple hypotheses testing. We illustrate the algorithm with a stylized example in Appendix D.

The outcome variable is the estimated firm-specific semi-elasticity of capital to the monetary policy shock, $\hat{\beta}_{i,3}$. We use thirty-five explanatory variables, including general firm characteristics such as sector, age, and various measures of firm size, details on capital and debt structure, profitability ratios, and growth rates of key variables. A full list is in Appendix D. To make these variables comparable to our estimated firm-specific elasticities, we compute their averages over time for each firm.

Figure 4. Predictors of firm-specific semi-elasticities.



Note: The variable importance of each explanatory variable for predicting the outcome variable, determined by the Random Forest. The outcome variable is firm-specific semi-elasticities of capital to monetary policy shocks, estimated from equation (2) at a horizon of $h = 3$ years after the shock. The explanatory variables are listed along the left side of the chart. "VA" denotes value-added. A detailed list of the explanatory variables is in Appendix D.2. The scale of the most important variable is normalized to one.

Figure 4 shows the outcome of the Random Forest algorithm: the relative importance of each firm characteristic for explaining the outcome variable (the value for the most important characteristic is normalized to one), which is called the "variable importance". This is based on how much the predictability of the estimated semi-elasticities declines if a variable is excluded from the analysis. The key result is that firm age is the most important predictor by a large margin. A firm's average fixed asset growth rate ranks a distant second, and other variables are further behind.

Alternative Random Forest specifications. We conduct three robustness checks, and list the results in Appendix D.3. First, we exclude explanatory variables that are highly correlated with other explanatory variables. The aim is to insure that a low importance for one variable does not simply reflect the presence of other correlated variables. Age remains the most important variable by a similar margin as in the baseline analysis. Second, we only use firms whose semi-elasticity estimates, $\hat{\beta}_{i,3}$, are statistically significant at the 90% level. In this case, age is the most important variable by an even larger margin than in the baseline analysis. Finally, we only use firms whose semi-elasticity estimates are based on at least ten observations.[11] In this case, a firm's fixed asset growth rate overtakes age as the most important variable, but age is still in second, and ahead of other variables by a wide margin. A possible explanation is that this restriction eliminates some young firms, which are crucial for the result based on the analysis in Section 4.3.

4.3 Transmission across firm age

We now investigate the relationship between a firm's age and its response to monetary policy shocks. Specifically, we group firm observations by their age—five-year age intervals up to age fifty, and then one group for firms over fifty—and for each group, run a separate estimation of the semi-elasticity of firms' capital stocks with respect to monetary policy shocks as in equation (1) (a firm is assigned to a group based on its age at the time of the shock, so it is assigned to different groups over time).[12] Thus, we estimate one semi-elasticity for each age group. We focus on a horizon of $h = 3$ years after the shock, in line with the rest of our heterogeneous effects analysis.

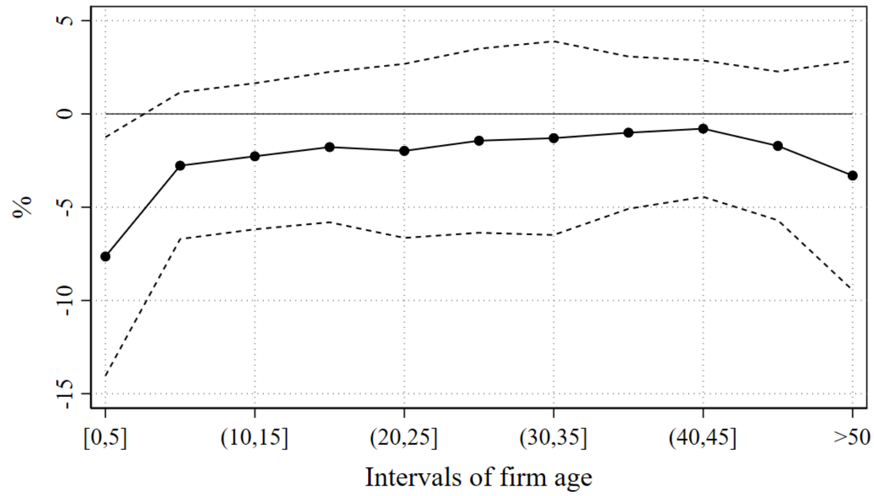
Figure 5 shows the implied response of a firm's capital stock to a 25 basis point increase in the interest rate, as a function of its age. It is most negative for the youngest firms, and increases toward 0 with age. The biggest change is between firms aged 0 to 5 years old and all older firms. In the former group, a firm's capital stock is 7.6% lower three years after the shock than it would be had the interest rate been unchanged, whereas capital is only 2.7%

[11] Ten is the average number of observations for firms for which we can estimate an elasticity at $h = 3$.

[12] In Appendix E, we use five-year age intervals up to one-hundred-fifty. For higher ages, the estimates are erratic and the confidence intervals are wide, which reflects that those groups contain fewer observations.

lower for firms aged 6 to 10 years old, and is 0.8% lower for firms aged 40 to 45. Moreover, the response is statistically significant at the 10% level only for the youngest firms. Finally, Figure 6 shows the difference in responses from Figure 5 between each age group and the youngest group. This difference is statistically significant at the 15% level for all groups.

Figure 5. Investment response across age groups at $h = 3$.

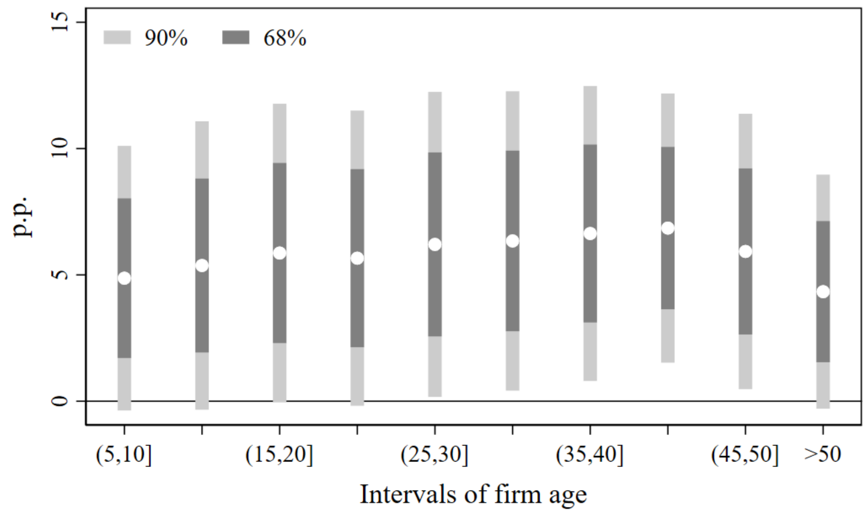


Note: The percentage response of firms' capital stocks to a 25 basis point contractionary monetary policy shock as a function of firm age interval, implied by semi-elasticities estimated separately for each age interval from equation (1) using a horizon of $h = 3$ years after the shock. An observation is grouped based on the firm's age at the time of the monetary policy shock, t. Each group contains five years except the first also includes zero, and the last includes all ages above fifty. The dashed lines form the 90% confidence interval, based on two-way clustered standard errors by firm and year-month.

Alternative specifications. We conduct a series of robustness checks, and list the results in Appendix E. In particular, we run the following variations on our baseline estimation of age-group-specific semi-elasticities: excluding exiters around each monetary policy shock; excluding entrants around each monetary policy shock; controlling for lagged firm size (measured by the log of total assets) and including an interaction term between the monetary policy shock and lagged firm size; excluding years after 2011 during which ECB engaged in unconventional monetary policy; excluding years after 2013 during which many speculated that the interest rate was at its lower bound; and controlling for a shadow rate measure of what the interest rate would be absent a lower bound.

The results are mostly unchanged; the biggest difference is that excluding exiters and excluding years after 2013 makes the gradient of the response with respect to age flatter

Figure 6. Differences in the investment response across age groups relative to the youngest group at $h = 3$.



Note: For each age group, the white dot is the difference between that age group's response from Figure 5 and the youngest age group's response. The light gray (dark gray) bars are the 90% (68%) confidence intervals, based on two-way clustered standard errors by firm and year-month.

and much more gradual. For the first case, this suggests that an increase in the probability of exiting for the youngest firms following a contractionary monetary policy shock is an important quantitative channel for our result.

4.4 Contribution to the aggregate response across firm age

Given the strong relative response of the youngest firms to monetary policy shocks, we now compute the share of the aggregate capital response for which they are responsible. Specifically, we can write the percentage change in the aggregate capital stock in response to a 25 basis point increase in the interest rate—at a horizon of $h = 3$ years after the shock in line with the rest of our heterogeneous responses analysis—as the capital-stock-weighted average of the capital stock percentage changes for different age groups:

$$\Delta K = \sum_j \omega_j \Delta k_j$$

where ΔK is the aggregate response, ω_j is group j's total capital stock relative to the aggregate capital stock, and Δk_j is the group j response. The weights $\{\omega_j\}$ are their averages across all years in our sample. Given the gradient in responses in Figure 5, we consider only five age groups: the same first three groups, firms aged 16 to 25, and firms older than 25.

The high sensitivity of young firms to monetary policy shocks is important for the aggregate response. The average of age group responses implies that the aggregate capital stock is 2.3% lower three years after a 25 basis point contractionary monetary policy shock than it would be had the interest rate been unchanged. The youngest firms aged 0 to 5 years old account for 35% of the aggregate response, even though their capital accounts for only 11% of the aggregate stock. By contrast, firms older than 25 are responsible for 43% of the aggregate capital stock, but only 22% of the aggregate response to monetary policy shocks.

5 Theoretical mechanisms

We now propose a theoretical framework based on capital adjustment costs to rationalize our finding that the responsiveness of a firm's capital stock to monetary policy shocks is declining with age. The model illustrates the mechanism, and is not quantitative. We provide empirical evidence in favor of our theory, and against other theories based on financial frictions.

5.1 A lifecycle firm model of investment

The model is of a single firm in partial equilibrium, i.e., holding fixed prices other than the interest rate, which we will exogenously shock. Time is discrete and infinite. Production is decreasing returns to scale in capital, the only factor of production. In each period, the firm chooses capital subject to the rental rate r, and adjustment costs: if capital is different from the previous period, then the firm must pay a convex cost that is proportional to the percentage change in capital, and a fixed cost that is independent of the size of the change. The firm maximizes the present discounted value of profits, using the interest rate r to discount future profits. The interest rate is both the discount rate as well as the capital rental rate; usually the rental rate includes the depreciation rate as well, which we omit for simplicity. The firm faces no risk.

Let $V(k)$ denote the firm's present discounted value of profits as a function of its capital stock in the previous period. It solves the following Bellman equation:

$$V(k) = \max_{k'}\{z(k')^{\alpha} - rk' - \Psi(k', k) + (1+r)^{-1}V(k')\}. \tag{3}$$

The firm used capital k in the previous period, and chooses capital k' in the current period. The first term is revenue—z is productivity and $\alpha \in (0, 1)$ captures decreasing returns to scale—the second term is the rental cost of capital, the third term is capital adjustment costs, and the last term is the discounted value of future profits. The adjustment cost function is

$$\Psi(k', k) = \chi_0 \mathbb{1}(k' \neq k) + \frac{\chi_1}{2} \left(\frac{k' - k}{k} \right)^2 k, \tag{4}$$

where the first term is the fixed cost, scaled by $\chi_0 \geq 0$, and the second term is the convex cost, scaled by $\chi_1 \geq 0$.

The firm's problem in each period can be decomposed into two stages: it chooses whether to adjust its capital, and then by how much. Therefore, write the value function as

$$V(k) = \max\{V_a(k) - \chi_0, V_n(k)\},$$

where $V_a(k)$ is the value function conditional on adjusting, i.e., choosing $k' \neq k$, and $V_n(k)$ is the value function conditional on not adjusting. Specifically,

$$V_a(k) = \sup_{k'} \left\{ z(k')^\alpha - rk' - \frac{\chi_1}{2} \left(\frac{k' - k}{k} \right)^2 k + (1+r)^{-1} V(k') \right\}$$

subject to $k' \neq k$, and

$$V_n(k) = zk^\alpha - rk + (1+r)^{-1} V(k),$$

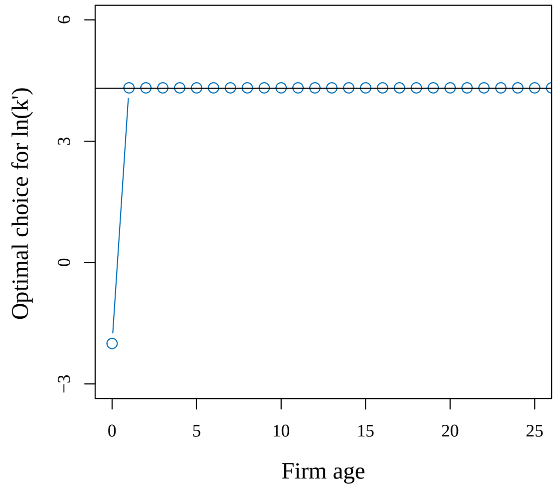
where capital is fixed at its previous level.

The firm lifecycle. The firm enters with an initial capital stock $k_0 > 0$, which we suppose is sufficiently small so that the firm grows over time. The firm's evolution is guided by two thresholds. First, $k^* \equiv (r/z\alpha)^{\frac{1}{\alpha-1}}$ maximizes revenue minus rental costs. Absent adjustment costs ($\chi_0 = \chi_1 = 0$), the firm immediately sets its capital stock to k^* and remains there forever. Second, with the fixed cost ($\chi_0 > 0$), there is a $\bar{k} < k^*$ such that if the firm's capital is in $(\bar{k}, k^*]$, then the benefit of adjusting is lower than the fixed cost.

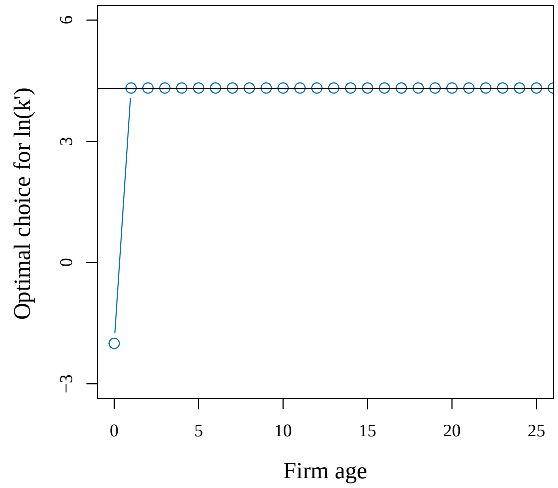
The firm's capital slowly increases over time (due to the convex adjustment cost) from k_0 until it is between $\bar{k}$ and k^*, at which point it remains constant forever. As such, the firm's age determines the distance between its capital and the optimal level k^*, and so whether it is paying its fixed adjustment cost.

Figure 7 shows the firm's log capital over its lifecycle for different types of adjustment costs. In each case, the solid black line is at the optimal level, k^*. In the absence of any adjustment costs (subplot a), the firm immediately sets $k = k^*$, and remains there forever.

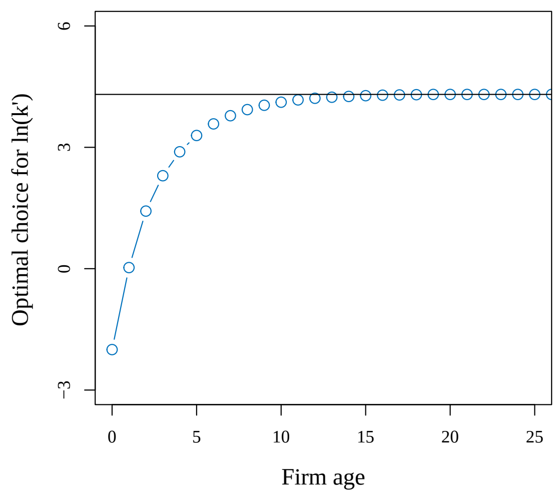
Figure 7. Capital choice across firm age.



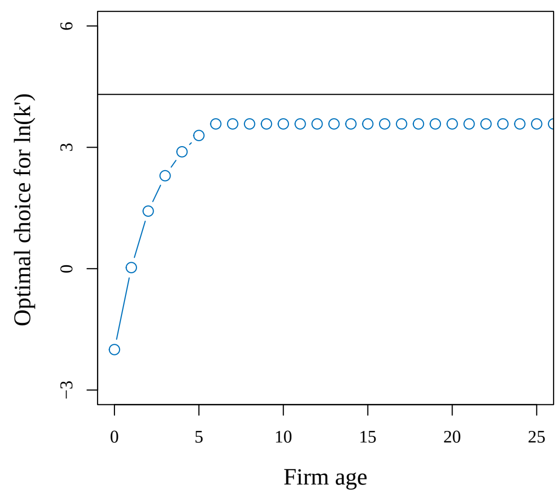
(a) No adjustment costs ($\chi_0 = \chi_1 = 0$)



(b) Fixed cost ($\chi_0 = 0.1,\ \chi_1 = 0$)



(c) Convex cost ($\chi_0 = 0,\ \chi_1 = 0.05$)



(d) All costs ($\chi_0 = 0.1,\ \chi_1 = 0.05$)

Note: The x-axis is firm age (periods since entry), and the y-axis is log capital. The blue dots show the policy function. The solid black line indicates the optimal capital stock, k^*, absent adjustment costs.

With only a fixed adjustment cost (subplot b), the firm still jumps immediately to its optimal size because the benefit of adjusting from its initial size exceeds the fixed cost. However, if the fixed cost were larger, the firm would remain at its initial size forever. Next, with only a convex adjustment cost (subplot c), the firm grows toward the same optimal size, but slowly because it is optimal to smooth adjustments over time. Moreover, the firm makes smaller percentage adjustments as it ages. Finally, with both adjustment costs (subplot d), the firm adjusts slowly because of the convex cost, and stops adjusting before it hits k^* because of the fixed cost. As the firm ages and approaches its optimal size, the value of adjusting shrinks, and eventually is less than the fixed cost. Importantly, the firm stops adjusting at a finite age, whereas with only convex adjustment costs, the firm slowly adjusts forever.

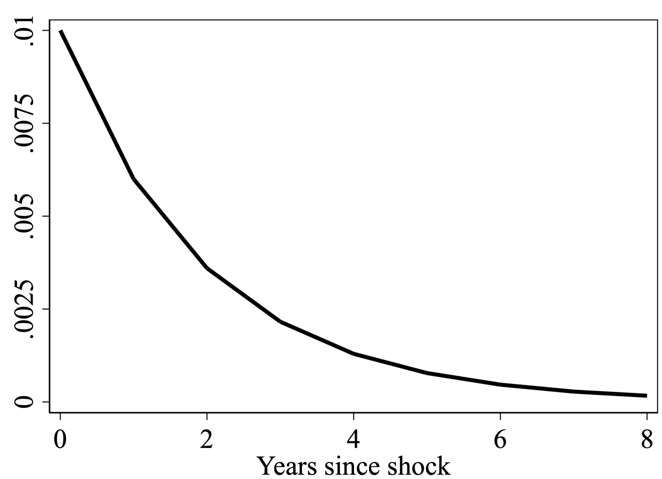
5.2 The effects of an interest rate shock

We now show that the model delivers our finding that younger firms' capital stocks are more responsive to interest rate shocks. We consider an unanticipated shock that moves the interest rate from r to $r + \varepsilon_0$, and dies out with persistence ρ:

$$r_t = r + \varepsilon_t \qquad \text{with} \quad \varepsilon_t = \rho\varepsilon_{t-1}, \tag{5}$$

where t is periods since the shock. Figure 8 shows the path of ε_t.

Figure 8. Path of interest rate shock.



Note: The evolution of the interest rate shock, which begins at 0.01 at $t = 0$, and has persistence $\rho = 0.6$.

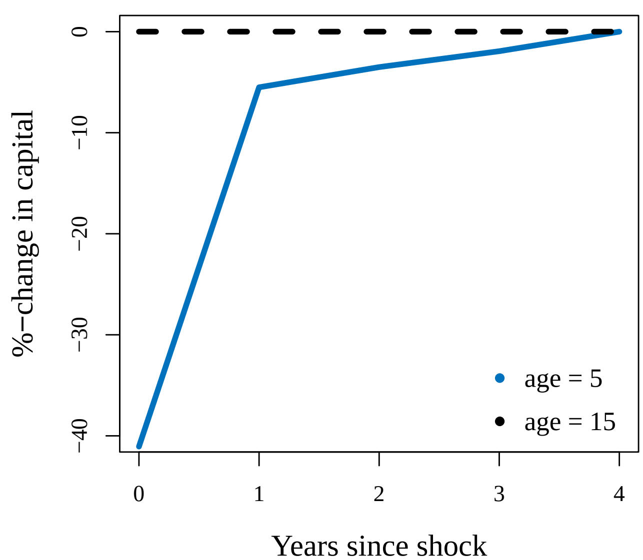
Formally, the firm's value function now solves the Bellman equation:

$$V(k, \varepsilon) = \max_{k'}\{z(k')^\alpha - (r + \varepsilon)k' - \Psi(k', k) + (1 + r + \varepsilon)^{-1}V(k', \rho\varepsilon)\},$$

where ε is the current interest rate shock, so $\rho\varepsilon$ is the shock in the following period. The interest rate shock increases the capital rental rate and the discount rate, both of which lower the firm's capital choice given its capital from the previous period. First, the higher rental rate increases the cost of capital, and so lowers the derivative of profits excluding adjustment costs with respect to capital. Second, part of the incentive to invest is to have more capital in the future because the firm's stock is below its optimal size, k^*. An increase in the discount rate lowers the significance of future profits, and so reduces this incentive.

Figure 9 shows the impulse response function of capital to the interest rate shock if the firm is young when the shock hits (solid blue line) and old when the shock hits (dashed black line). The young firm's capital is immediately lower than it would have been without the shock, and converges back to its initial path as the shock fades. On the other hand, the old firm's capital is unaffected. Intuitively, the young firm pays its fixed adjustment cost regardless of the shock, so it responds to changes in the capital rental cost and in the discount rate. The old firm would not have paid its fixed cost absent the shock, and does not with the shock either. The shock is sufficiently small that the value of responding does not outweigh the fixed cost. Moreover, since the shock is temporary, the firm is reluctant to pay the fixed cost to decrease its capital stock just to pay again later to increase it.

Figure 9. Responses to the interest rate shock across firm age.



Note: The x-axis is periods since the initial shock to the interest rate, and the y-axis is the percentage change in the path of the firm's capital with the shock from what it would have been without the shock. The blue solid line and black dashed lines are if the firm was 5 periods old and 15 periods old, respectively, in the initial period of the shock. The model features fixed and convex adjustment costs ($\chi_0 = 0.1,\ \chi_1 = 0.05$).

Age vs. size. Our Random Forest algorithm found that a firm's age is a much more significant predictor than its size of its response to monetary policy shocks. Moreover, our estimated age-group-specific semi-elasticities to monetary policy shocks are mostly the same whether or not we control for firm size and include an interaction term between size and the monetary policy shock. However, in the model, there is an exact relationship between firm age and size, so it does not distinguish between the two. Nonetheless, we argue that our mechanism speaks more to the importance of age than size.

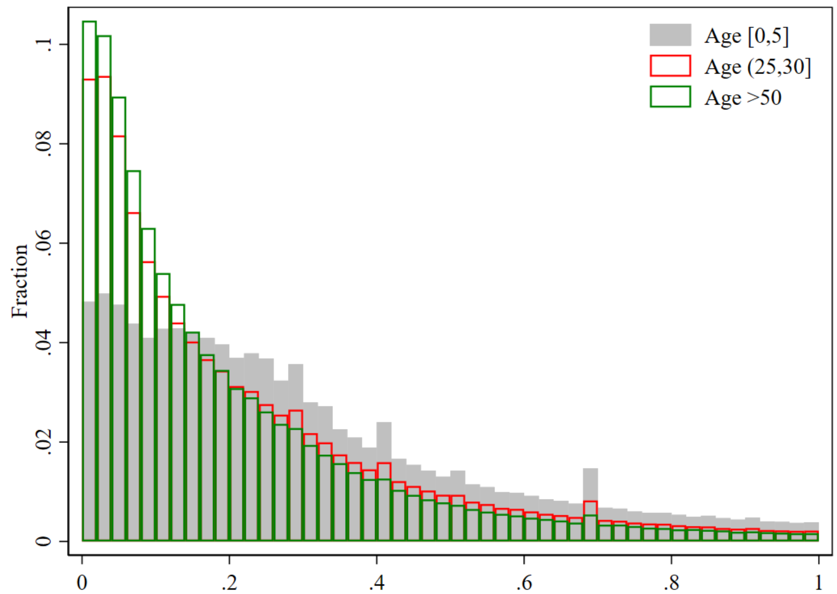
Specifically, we can break the equivalence between age and size by extending the model to a distribution of firms with different levels of permanent productivity. As in the baseline model, a firm grows over time toward its optimal size. A firm's responsiveness to interest rate shocks depends on the distance between its current size and its optimal size. Thus, young firms are more responsive than old firms because they have had less time to grow. This holds regardless of current size because, for example, if a young firm is large, then it must be productive, and so have a large optimal size as well. On the other hand, the relationship between a firm's size and its responsiveness to interest rate shocks is murkier. A small firm may be young and hence far from its optimal size, in which case it is responsive. But it may also be an unproductive firm with a small optimal size, in which case it is not so responsive.

General equilibrium effects. Our empirical results may include general equilibrium effects as well as the direct effects of changes in the interest rate on firms' investment decisions. In our model, we only consider the latter. Nonetheless, if general equilibrium effects go in the same direction as direct effects—for example, if an increase in the interest rate depresses demand for a firm's goods—then the qualitative results would be the same. In particular, younger firms would be more responsive. This is because a fall in demand in our model is equivalent to a fall in productivity, z, which has the same effect on a firm's capital choice as a rise in the capital rental rate.

5.3 Testable model predictions

We compare two key predictions of our theory to the data. First, in the theory, younger firms are more likely than older firms to adjust their capital stocks. This implies that younger firms are more likely to pay fixed adjustment costs, which makes them more responsive to monetary policy shocks. Using our data, Figure 10 shows the distribution of absolute changes in fixed assets for different firm ages. Older firms' investments are much more bunched near zero; for example, firms older than 50 years old are more than twice as likely as firms 0 to 5 to change their capital stocks by less than 5%. Moreover, there is a much bigger difference between firms 0 to 5 and firms 25 to 30 than between the latter group and firms older than 50, as was the case in Figures 5 and 6 on the responsiveness of firms to interest rate shocks.

Figure 10. Distribution of fixed asset growth magnitudes across age groups.

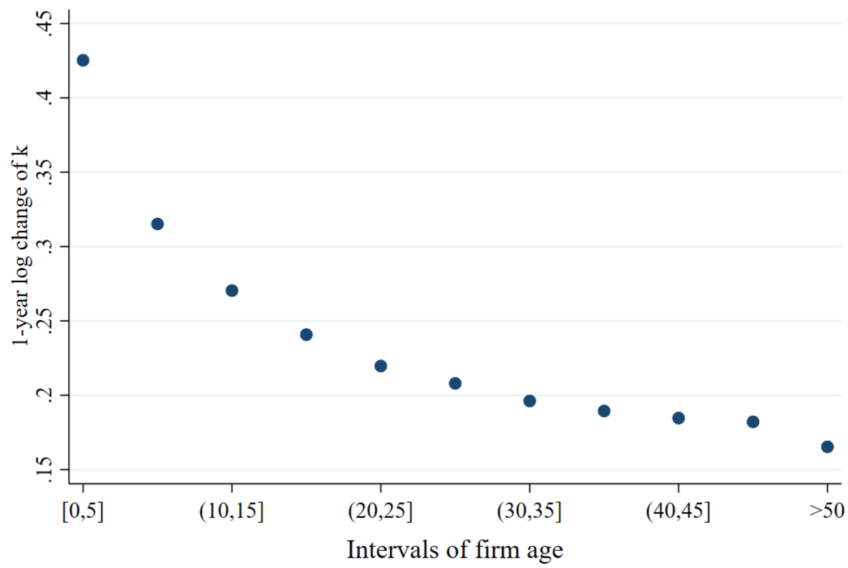


Note: The distribution of absolute values of annual total fixed asset growth rates for three firm age groups: at most 5 years old (gray), between 25 and 30 years old (red), and older than 50 (green). The x-axis is the absolute value of the change in fixed assets relative to fixed assets in the previous year. The y-axis is the fraction of firms in each of fifty bins; values greater than 1 (100%) are excluded.

Second, in the theory, younger firms' capital stocks grow faster than older firms'. This underlies the first prediction because it implies that older firms have less incentive to pay their fixed costs to adjust. Using our data, Figure 11 shows the median of positive annual growth rates in total fixed assets by firm age. Conditional on growing, younger firms are more likely to grow quickly; for example, the median is close to 45% for firms between 0 and 5 years old, and below 20% for firms older than 30. The median falls steadily with age and once again, as with the responsiveness of firms to interest rate shocks, the largest fall is from firms 0 to 5 years old and firms 5 to 10 years old. Finally, the pattern holds when *(i)* controlling for firm size (Figure F.1 in Appendix F) and *(ii)* considering within-firm variation by regressing median positive annual growth rates on age and a firm fixed effect.

This evidence is in line with the finding in Haltiwanger et al. (2013) that younger firms tend to grow faster, whether or not they control for firm size.

Figure 11. Median positive fixed asset growth rates by firm age.



Note: The median of annual growth rates in fixed assets for different firm age groups, only considering positive growth rates.

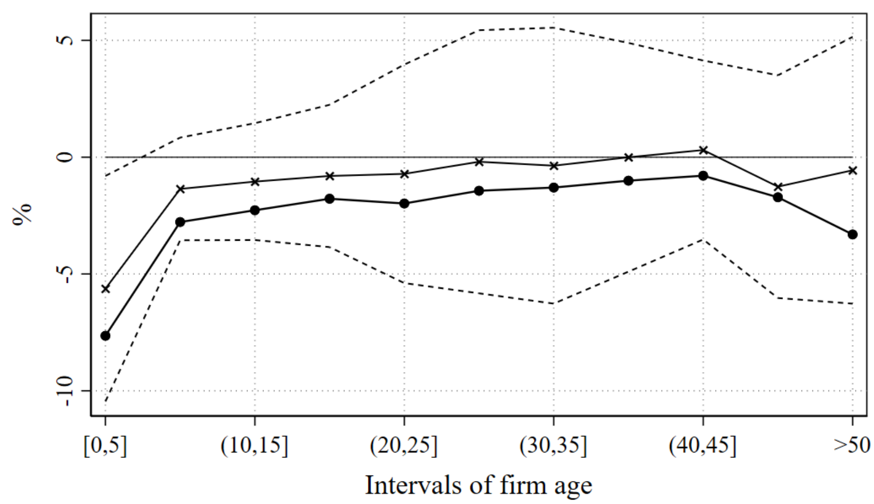
5.4 Alternative mechanism: financial frictions

Our proposed mechanism for rationalizing heterogeneous responses to monetary policy across firm age relies solely on capital adjustment frictions. The most prominent theory for monetary policy transmission heterogeneity across firms relates to financial frictions (see, for example, Gertler and Gilchrist (1994), Jeenas (2019), Ottonello and Winberry (2020), Cloyne et al. (2022) and Durante et al. (2022)). The idea is that monetary policy shocks affect borrowing costs and the value of collateral that firms use to obtain external credit. This can generate heterogeneous responses if some firms' investments are more sensitive to the availability of credit, or if some firms' borrowing costs or collateral values are more sensitive to monetary policy.

We now provide evidence that financial frictions cannot explain our empirical findings. This aligns with the findings of our Random Forest algorithm that various measures of a firm's financial position are much less important than its age for predicting its response to monetary policy shocks. We do not test whether financial frictions generate heterogeneous responses to monetary policy across firms *in general*, but only whether they can explain the particular heterogeneity we find, namely that younger firms are more responsive to monetary policy shocks. That said, the results from our Random Forest algorithm suggest that this heterogeneity is particularly important.

First, if financial frictions explain our results, then the difference in responsiveness to monetary policy shocks across firm age should be lower when controlling for measures of firms' financial constraints. Thus, we rerun our estimation of age-group-specific semi-elasticities of firms' capital stocks with respect to monetary policy shocks (Section 4.3), but control for a proxy for firms' one-year-lagged financial constraints (one year before the monetary policy shock), and include an interaction term between the lagged proxy and the monetary policy shock. We consider two proxies separately: for a collateral-based constraint, we use a firm's ratio of total debt to total assets; and for a cashflow-based constraint (which Lian and Ma (2020) and Drechsel (2023) find to be important), we use a firm's ratio of total debt to EBITDA (earnings before interest, taxes, depreciation, and amortization). Figures 12 and 13 show the implied responses of firms' capital stocks to a 25 basis point increase in the interest rate by firm age. In each case, the pattern of responsiveness across firm age is mostly unchanged from our baseline results, and if anything is stronger.

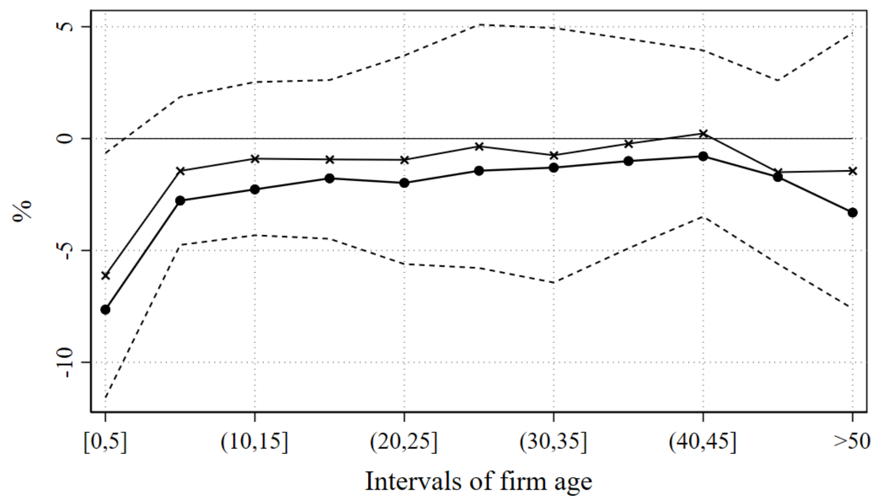
Figure 12. Investment response across age groups, controlling for debt-to-assets ratio.



Note: The solid line with x-markers is from Figure 5. The solid line with dots is the same, but controlling for a firm's ratio of total debt to total assets in $t-1$ (where the monetary policy shock is at t), and an interaction term between that ratio at $t-1$ and the monetary policy shock at t.

Next, Bahaj et al. (2022) put forward a particular theory that links financial frictions to a higher responsiveness of younger firms to monetary policy shocks. Specifically, they find that younger firms more often use the private home of the firm owner as collateral, and that housing values are particularly sensitive to monetary policy. More abstractly, this suggests

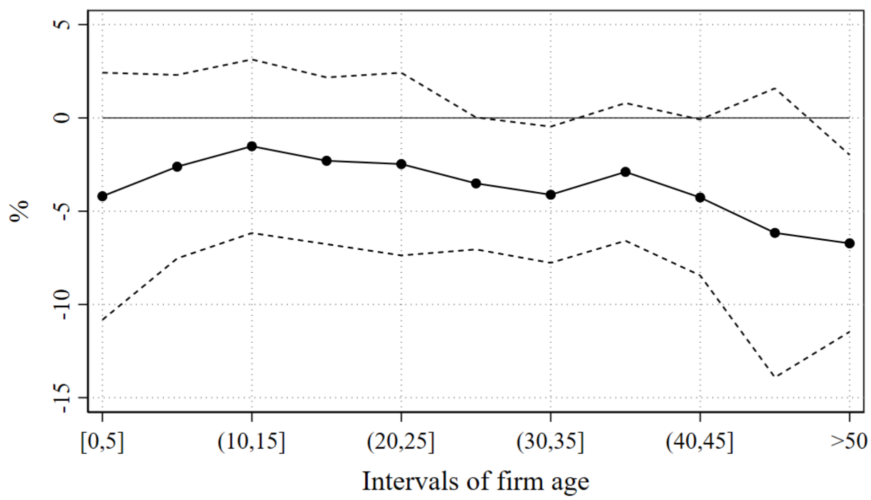
Figure 13. Investment response across age groups, controlling for debt-to-EBITDA ratio.



Note: The solid line with x-markers is from Figure 5. The solid line with dots is the same, but controlling for a firm's ratio of total debt to EBITDA in $t-1$ (where the monetary policy shock is at t), and an interaction term between that ratio at $t-1$ and the monetary policy shock at t.

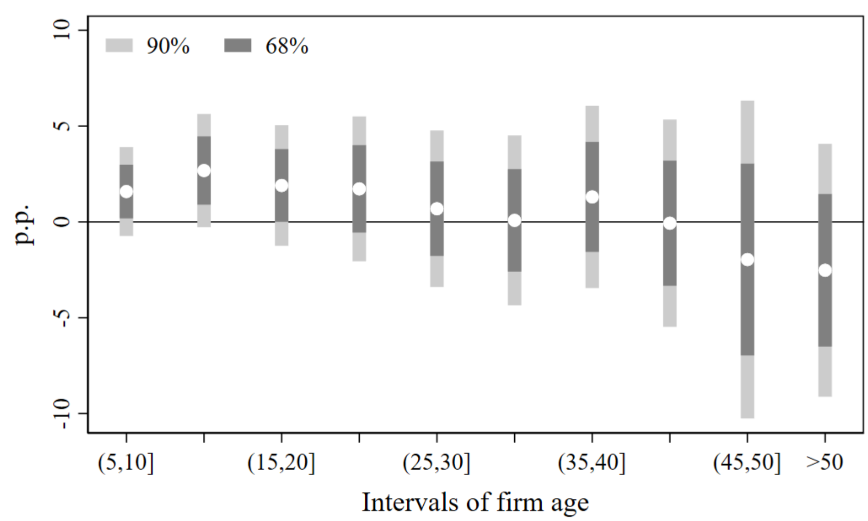
that younger firms are more responsive because the value of their collateral is more sensitive to monetary policy. To test whether this explains our empirical results, we estimate age-group-specific semi-elasticities of firms' total debt with respect to monetary policy shocks; we use a horizon of $h = 1$ year after the shock because if we estimate one semi-elasticity for all firms, then its magnitude peaks after 1 year (see Figure F.2 in Appendix F). If financial frictions are behind our results through the particular mechanism described, then younger firms' debts should be more responsive. Figures 14 and 15 show the implied response of firms' debts to a 25 basis point increase in the interest rate across different age groups, and the difference in each age group's response from the youngest firms'. Although the youngest firms' debts fall by more than the debts of firms 5 to 25 years old—in line with the described mechanism—they fall by less than the debts of firms older than 25 years old—against the described mechanism. Moreover, the difference of each age group's response from the youngest group's is not statistically significant at the 90% level, and the differences are only significant at even the 68% level for firms between 5 and 10 years old.

Figure 14. Debt response across age groups at $h = 1$.



Note: The same as Figure 5, except using a horizon of $h = 1$ years after the shock, and using the cumulative change in the log of firms' debts as the outcome variable rather than in the log of their capital stocks.

Figure 15. Differences in debt response across age groups relative to the youngest group at $h = 1$.



Note: The same as Figure 6, except using a horizon of $h = 1$ years after the shock, and using the cumulative change in the log of firms' debts as the outcome variable rather than in the log of their capital stocks. The light gray (dark gray) bars show the 90% (68%) confidence intervals.

6 Conclusion

We use machine learning techniques to detect firm age as the most important driver of heterogeneity in firm-level investment responses to monetary policy shocks. Regression analysis based on impulse response functions confirms that younger firms show a significantly higher sensitivity to central bank policy than older firms. We rationalize our findings in a simple model with fixed and convex capital adjustment costs. Intuitively, younger firms are still growing, and so pay their fixed costs regardless of monetary policy. Thus, they are ready to respond to changes in their environment. Older firms are not paying their fixed adjustment costs, and so do not respond.

The findings are informative for policymakers in two ways. First, they suggest that the distribution of firm age in the economy can be a factor that leads to differences in aggregate transmission across countries or over time. In particular, in the euro area, where there is one central bank presiding over many countries at a time, this would imply that transmission is stronger to countries with a larger share of young firms. Second, given the recent fall in dynamism and firm entry, our theory predicts that monetary policy has become less potent.[13]

Our paper suggests that more research is warranted into the role of real frictions, such as capital adjustment costs, for monetary policy transmission. Many papers investigate the role of financial frictions in this context, but there is less work on the importance of other frictions that shape firms' investment decisions. More generally, our paper shows the power of novel statistical methods like machine learning for detecting drivers of micro-level heterogeneity. It would be interesting to use these techniques to investigate the dynamics of employment and consumption as well.

[13] A slight shift in the distribution of firm age towards older firms can be seen in our data in Figure A.2 in Appendix A.3. This is also mirrored in a fall in the share of observations of young firms shown in Figure A.3.

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Appendices

A Data details

A.1 Variables and transformation

Table A.1: Detailed data overview.

Variable	Description and transformation	Source
Firm-level variables		
Investment	Cumulative percentage change in total fixed assets over h-years	Orbis (*TFAS*)
Firm age	Difference of the date of incorporation and the year of reporting	Orbis
Employment	Number of employees	Orbis (*EMPL*)
Sales	Operating revenue	Orbis (*OPRE*)
Firm size	Log of total assets	Orbis (*TOTA*)
Debt	Sum of short-term debt and long-term debt	Orbis (*LTDB, LOAN*)
Leverage	Ratio of total debt to total assets	Orbis (*LTDB, LOAN, TOTA*)
Monetary policy shock		
3-month OIS	High-frequency surprises; full event window; only surprises where change in stock price moves in opposite direction as change in short-term rate; aggregated to annual frequency via twelve month moving sum	EA-MPD Altavilla et al. (2019)
Aggregate variables		
HICP index	Country-level, monthly series; year-on-year percentage change except for deflating where index is used; base year 2015	SDW (*ICP.M.?.N. 000000.4.INX*)
Industrial production index	Country-level, monthly series; year-on-year percentage change	Eurostat (*STS_INPR_M*)

Note: The data identifiers are given in parentheses. A "?" in the identifier is to be replaced with the two-letter country code. All firm-level observations have been deflated with the monthly HICP index for the respective country, where the base year is 2015. In addition, they are winsorized at the 1% and the 99% level. SDW refers to the ECB Statistical Data Warehouse.

A.2 Coverage and representativeness

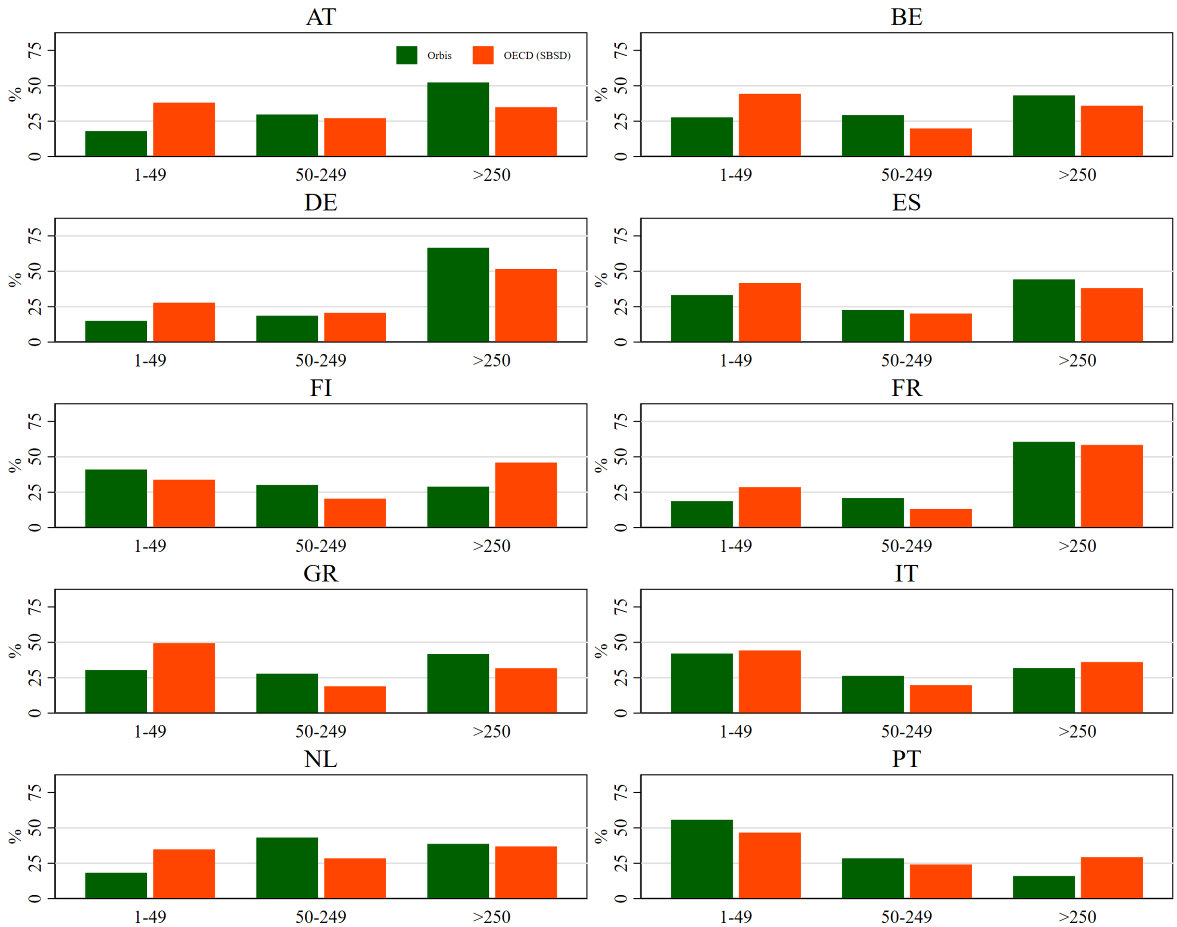
To evaluate the coverage and representativeness of the Orbis data, we follow the exercise presented in Kalemli-Özcan et al. (2019) (see in their paper Table 1 for coverage, Table 2 for representativeness and Appendix C for further details). The comparison is conducted along aggregate "Gross output", which is equivalent to firms' gross sales. As benchmark for the aggregate economy, we use data from the OECD Structural Business Statistics Database (SBSD), which is available for different sectors and across firm size classes (by employment) from 2005 onward. We use the most aggregate sectoral composition of non-financial firms referred to as "Business economy, except financial and insurance", which is composed of sectors with NACE letters B to N, excluding K (finance and insurance). In order to match the aggregate data, the Orbis sample is restricted to these sectors for the comparison exercise. For the representativeness, reported in Figure A.1, the sample is further restricted to firm-year observations with non-missing entries for the number of employees.

Table A.2: Coverage of the aggregate business economy based on gross output.

	AT	BE	DE	ES	FI	FR	GR	IT	NL	PT
2005	26.21	67.93	47.87	80.63		78.74		69.24	30.29	64.26
2006	52.44	66.01	50.19	82.49	55.41	78.74		70.95	30.90	66.96
2007	56.97	63.92	48.50	80.76	55.90	79.98		73.00	31.84	66.97
2008	58.48	65.74	48.79	81.26	54.84	78.30		70.35	32.47	66.07
2009	59.73	64.99	45.35	81.85	54.68	77.72	53.41	74.26	30.79	66.48
2010	66.63	61.25	47.46	85.74	55.15	77.93	54.47	72.06	32.09	68.14
2011	66.71	60.96	48.38	85.42	57.24	79.00	57.93	73.19	33.07	66.06
2012	68.64	61.60	48.29	86.43	55.57	79.94	58.81	68.51	34.00	65.49
2013	71.53	62.47	48.48	87.67	55.72	78.74	56.79	69.55	34.47	66.17
2014	73.39	62.81	44.51	87.72	57.44	77.70	59.41	69.86	34.44	67.30
2015	72.17	64.54	42.93	86.28	59.60	73.79	57.25	71.17	30.97	68.40
2016	68.79	63.47	43.40	86.29	61.47	69.90	61.57	73.03	30.13	68.95
2017	72.22	63.62	45.35	86.81	63.34	74.43	60.72	74.57	29.83	68.91
2018	73.57	64.34	44.94		62.54	72.09		74.79	28.29	67.48
Average	63.39	63.83	46.75	84.56	57.61	76.93	57.82	71.75	31.68	66.97

Note: Comparison along the Orbis variable "Operating revenue (OPRE)" vs. OECD SBSD variable "Turnover" by country and year. To calculate the share of the Orbis sample in the aggregate business economy, the sectors have been restricted to match those of the SBSD data (NACE letters B to N, excluding K). Missing entries and time limitations are due to restrictions of the SBSD data.

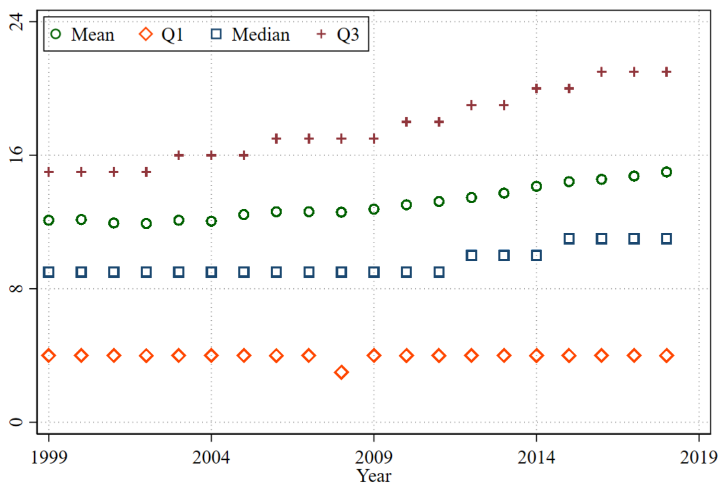
Figure A.1. Representativeness of the firm size distribution based on gross output.



Note: Comparison along the Orbis variable "Operating revenue (OPRE)" vs. OECD SBSD variable "Turnover" by country for the year 2017. The green bar is the fraction of gross output by firms in a size bin from the Orbis data and the orange bar for the SBSD data respectively. The x-axis shows buckets of firm size by number of employees. In the Orbis data, the sectors have been restricted to match those of the SBSD data (NACE letters B to N, excluding K) and the sample is limited to firm-year observations where information on the number of employees is available.

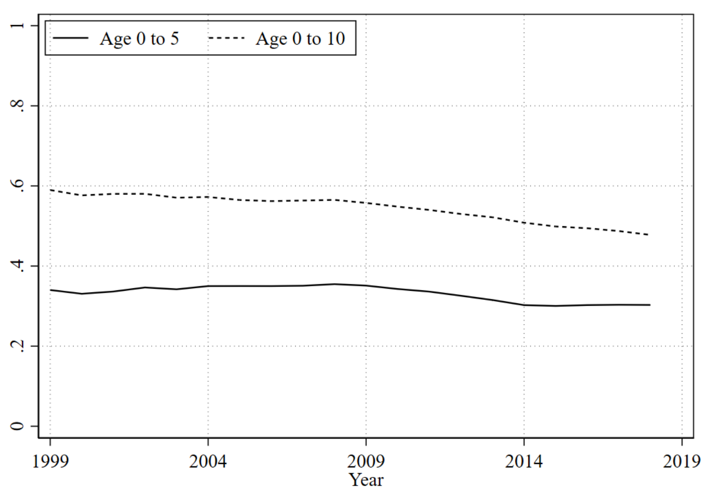
A.3 Additional descriptives

Figure A.2. Distribution of firm age over time.



Note: The figure shows statistics on the distribution of firm age in the sample over time. The mean (median) is given by the circle (square) and the first and third quartiles are shown as diamond and cross respectively.

Figure A.3. Share of young firms over time.

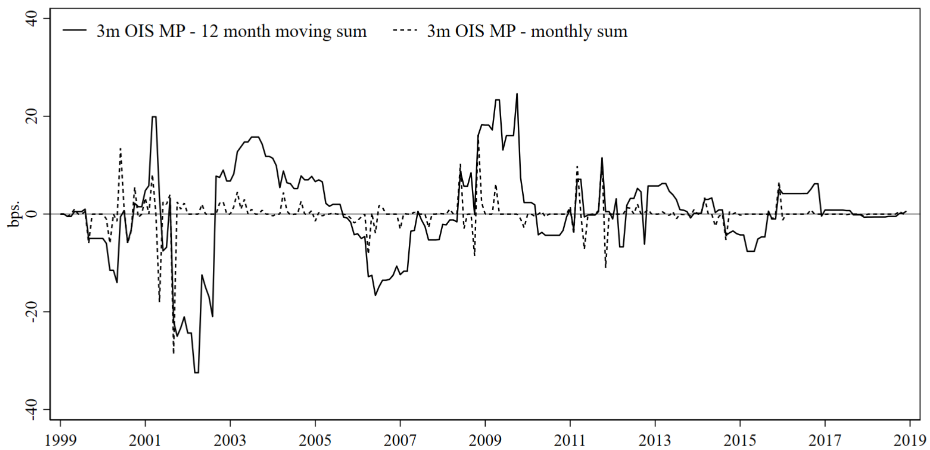


Note: The figure shows the share of sample observations of young firms over time. The solid line is the share of firms of age zero to five and the dashed line is the share of firms of age zero to ten.

B Identification

B.1 Time series of monetary policy shocks

Figure B.1. Time series of monetary policy shocks.



Note: The figure shows the time series of the identified monetary policy shock. The solid line presents the twelve-month moving sum of the 3-month OIS rate surprises. The dashed line is the underlying monthly series of 3-month OIS rate surprises. The monetary policy shocks have been identified from the negative cross-asset correlation in the interest rate and stock prices around ECB Governing Council meetings as detailed in subsection 3.1.

B.2 Aggregate transmission at monthly frequency

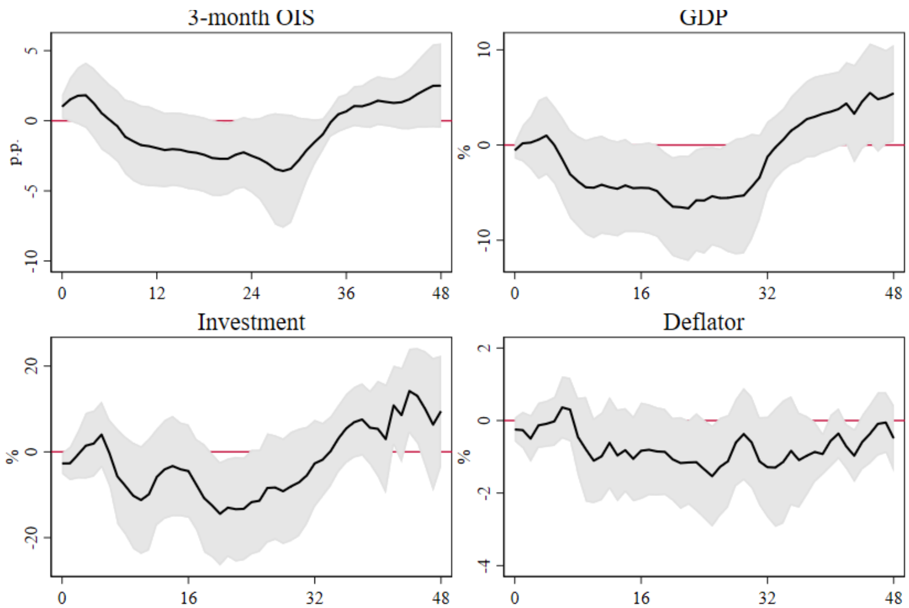
The impulse responses depicted in Figure B.2 are obtained from local projections (Jordà, 2005) estimated on a country panel of the ten euro area countries that are represented in the firm-level data. The estimation equation is given by

$$\Delta_h Y_{j,t+h} = \alpha_{j,h} + \beta_h shock_t^{MP} + \Gamma_h' X_{t-1} + \epsilon_{j,t+h} \tag{6}$$

where j is the country, t the month and h the projection horizon. The outcome variables are the changes in the three month OIS rate - which is the same across all countries -, log GDP, log investment and log deflator in period $t+h$ relative to period $t-1$. The monetary policy shock series is identified as laid out in subsection 3.1 of the main text where the event-level surprises have been aggregated to monthly frequency after evaluating the cross-correlation in surprises between the interest rates and the equity index. $\alpha_{j,h}$ is a country fixed effect and X_{t-1} a set of common controls including euro area GDP and deflator as well as interest rates and lags of the monetary policy shock series. Standard errors are computed using the Driscoll and Kraay (1998) method.

The underlying data are given as follows: The OIS rate is the monthly average of daily observations. The data for GDP, investment and the deflator has been interpolated from quarterly frequency to monthly frequency using the Chow and Lin (1971) method. The monthly series along which the interpolation has been performed are industrial production, construction and the HICP index respectively.

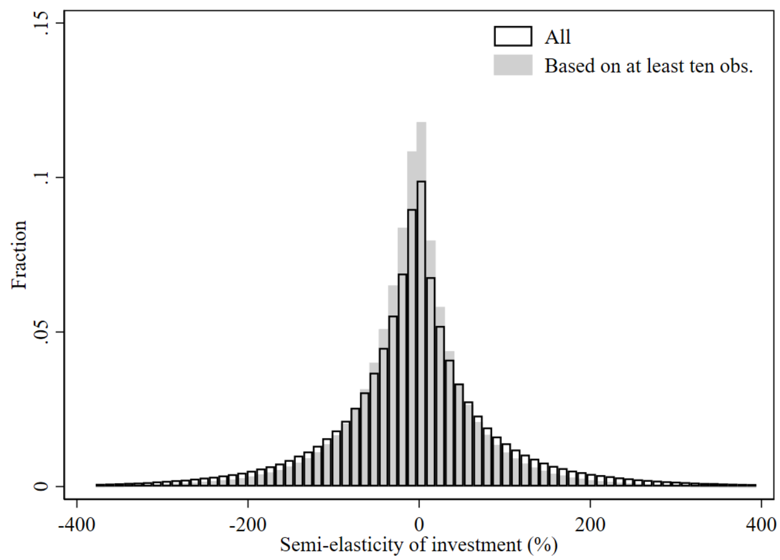
Figure B.2. Aggregate impulse responses.



Note: The figure shows impulse response functions from local projections estimated from aggregate data on a panel for ten euro area countries at monthly frequency. The investment series contains investments from all domestic sectors including the government. The responses have been normalized to a 100*bps* increase in the 3-month OIS rate on impact. The gray area is the 90% confidence interval and the x-axis shows the months after the monetary policy shock.

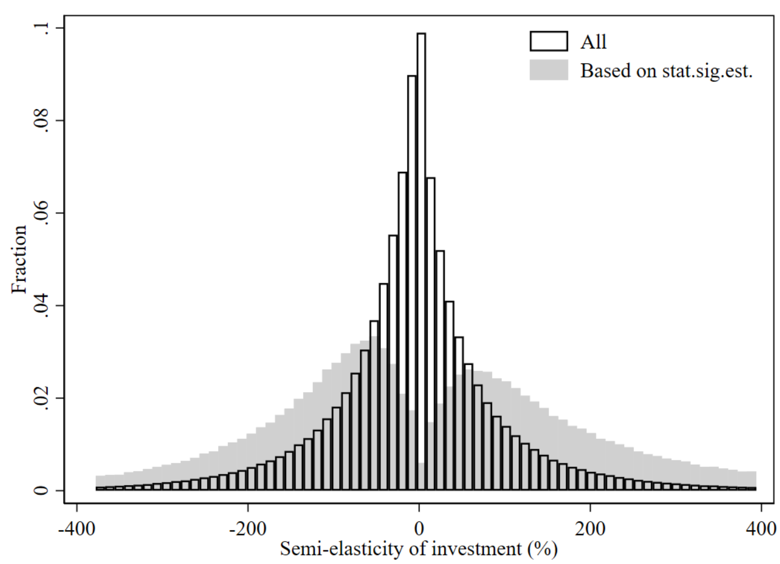
C Capital semi-elasticities

Figure C.1. Histogram of firm-specific investment responses at $h = 3$ for all firms vs. firms with at least ten observations.



Note: The transparent bars are the same as Figure 3. The gray bars are the same, but only using the subsample of semi-elasticities that are estimated for firms with at least ten observations.

Figure C.2. Histogram of firm-specific investment responses at $h = 3$ for all firms vs. firms with statistically significant semi-elasticities.



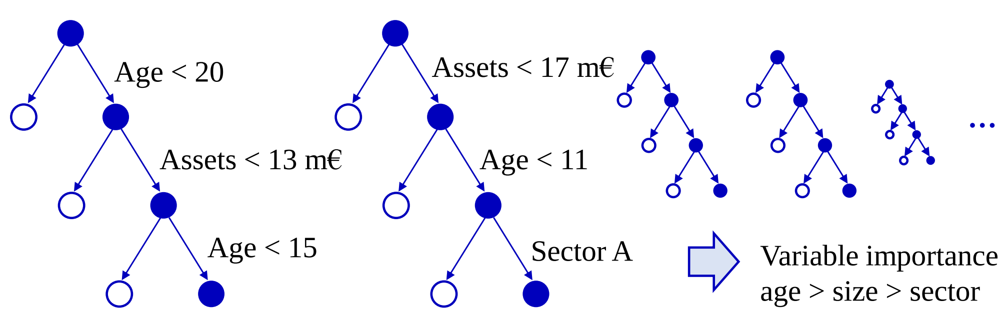
Note: The transparent bars are the same as Figure 3. The gray bars are the same, but only using the subsample of semi-elasticities that are statistically significant at the 90% level.

D Random Forest

D.1 Illustrative example of the algorithm

This subsection presents a stylized example of the Random Forest algorithm. Figure D.1 shows a hypothetical sketch of the procedure. In the example, the dependent variable Y_i is the investment elasticity of firm i with regard to monetary policy and there are three observable firm characteristics $X_i = \{size, age, sector\}$. Starting from a random draw (bootstrapped with replacement) of the full sample, the algorithm will process each subsample separately and asses multiple times at which sample split along X_i the variation in Y_i is maximized, similar to the logic of a decision tree. For continuous variables, the threshold for the sample split is endogenously determined. The procedure is continued along the respective subsamples obtained from splitting the sample until an endpoint is reached (the depth of the tree is a pre-specified input). In accordance with the name of the algorithm, multiple of these trees are created from the different subsamples and together they constitute a forest. Across all trees, the algorithm then summarizes the relative importance of the potential explanatory variables for creating variation in the outcome variable. This so-called "variable importance" is reported, with a normalization relative to the most important variable, which is scaled to one. The variable importance of the other variables is expressed relative to the most important variable.

Figure D.1. Stylized example of Random Forest algorithm.



D.2 List of explanatory variables

We now list the set of explanatory variables considered in the Random Forest algorithm described in Section 4.2. For all time-varying variables, the time-average over all observations for firm i has been calculated to map them into a single firm-specific elasticity. All financial variables are in real terms and winsorized at the top and bottom 1%.

General firm characteristics: age, size (total assets, gross sales, value added, employees), sector

Capital structure & liquidity: cash and equiv./total assets, cashflow/gross sales, fixed asset share, current asset share

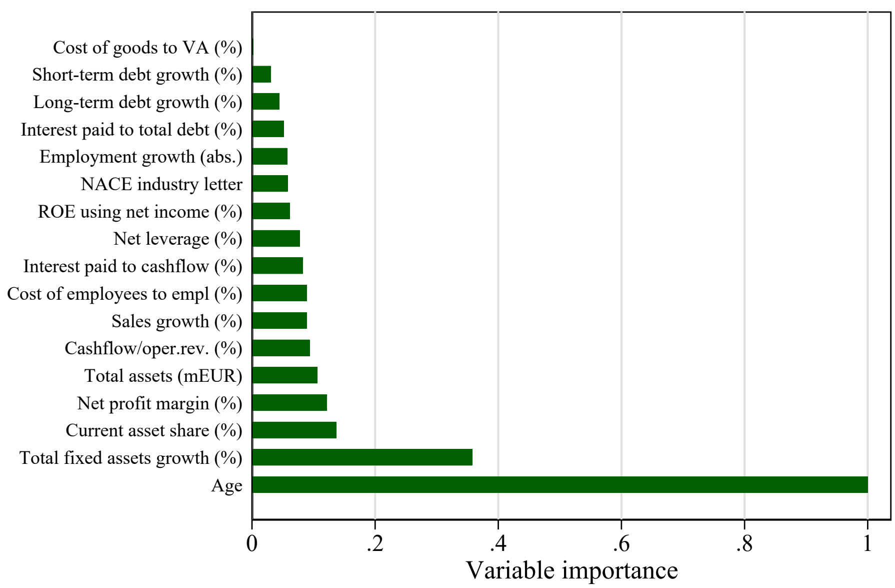
Debt structure, debt growth and interest burden: leverage (total liabilities/total assets), net leverage ((total liabilities - cash)/total assets), financial debt/total assets, short-term debt share, short-term debt growth, long-term debt growth, interest paid/financial debt, interest paid/cashflow

Profitability and margins: net income/total equity (ROE), net income/total assets (ROA), net income/gross sales, EBIT/gross sales, EBITDA/gross sales, EBITDA/total assets, gross sales/employees, wage bill/employees, wage bill/value added, cost of goods/value added

Growth (yoy): total assets, employment (also in absolute terms), gross sales, value added, fixed assets

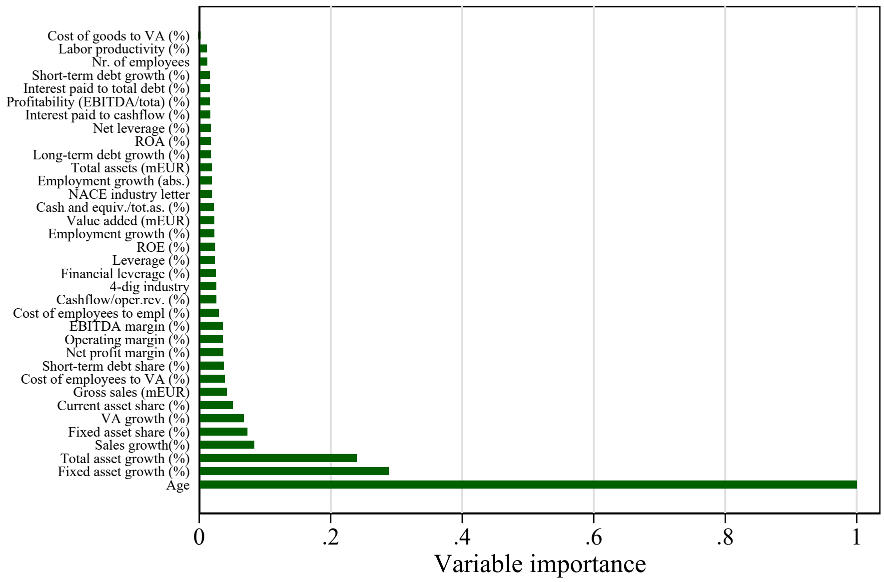
D.3 Random forest on alternative subsamples and covariates

Figure D.2. Predictors of firm-specific semi-elasticities using a smaller set of explanatory variables.



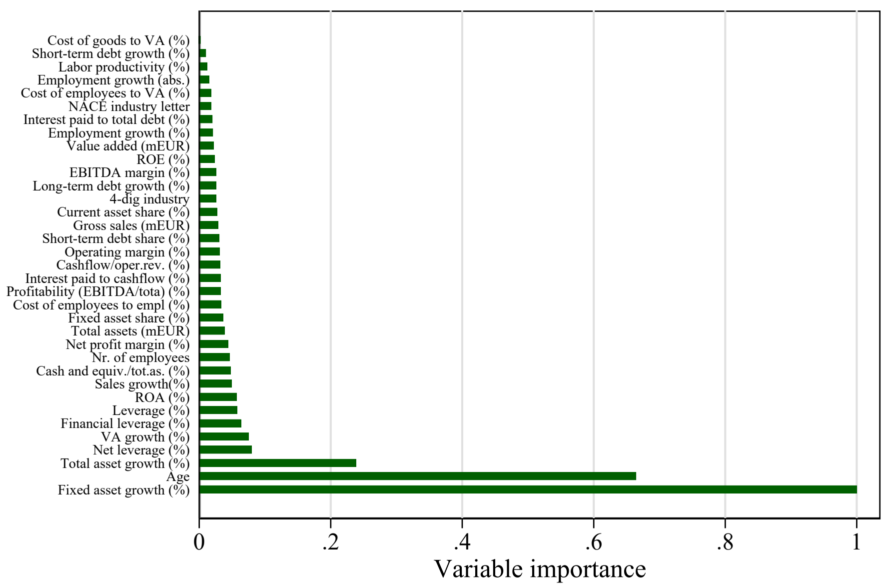
Note: The same as Figure 4, but using a smaller set of explanatory variables.

Figure D.3. Predictors of firm-specific semi-elasticities using the subset of statistically significant semi-elasticities.



Note: The same as Figure 4, but only using the subsample of semi-elasticities that are statistically significant at the 90% level.

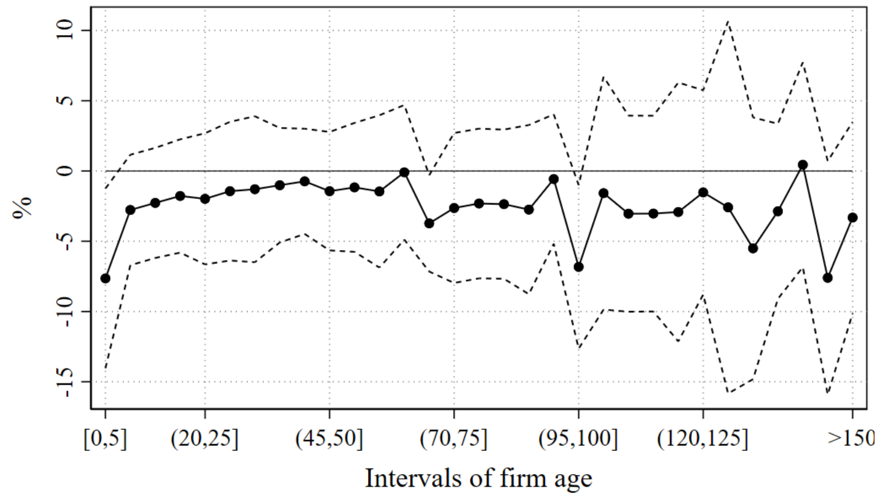
Figure D.4. Predictors of firm-specific semi-elasticities using the subset of semi-elasticities estimated from at least ten firm-level observations.



Note: The same as Figure 4, but only using the subsample of semi-elasticities that are estimated for firms with at least ten observations.

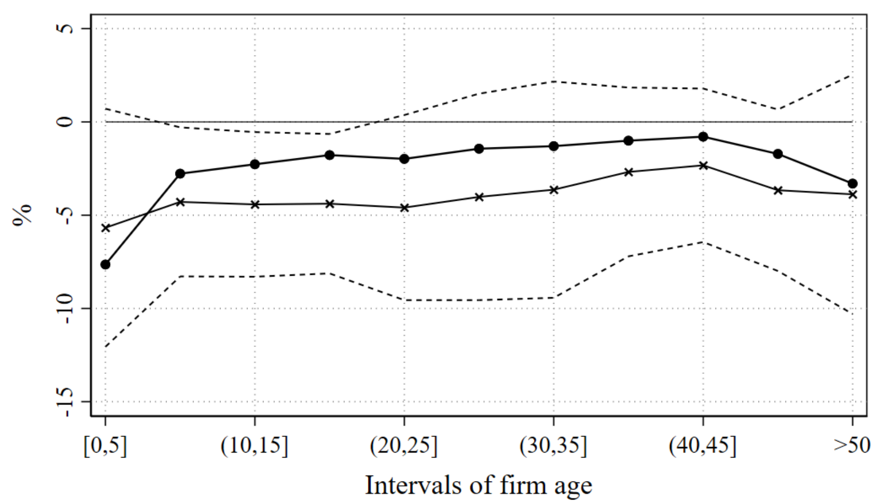
E Additional figures for main findings

Figure E.1. Investment response across age groups at $h = 3$, extended to age 150.



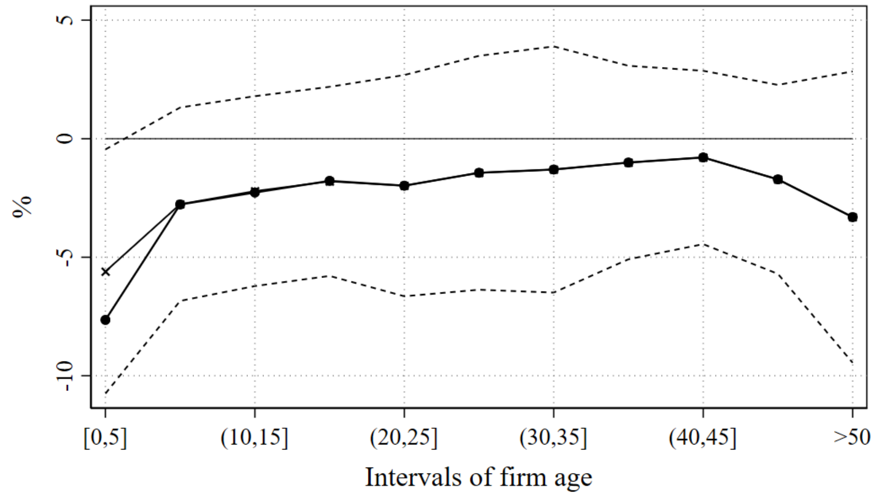
Note: The same as Figure 5, but with the oldest age group split into five year intervals up to age one-hundred-fifty, and then a final group for all firms older than one-hundred-fifty.

Figure E.2. Investment response across age groups at $h = 3$, excluding exiting firms.



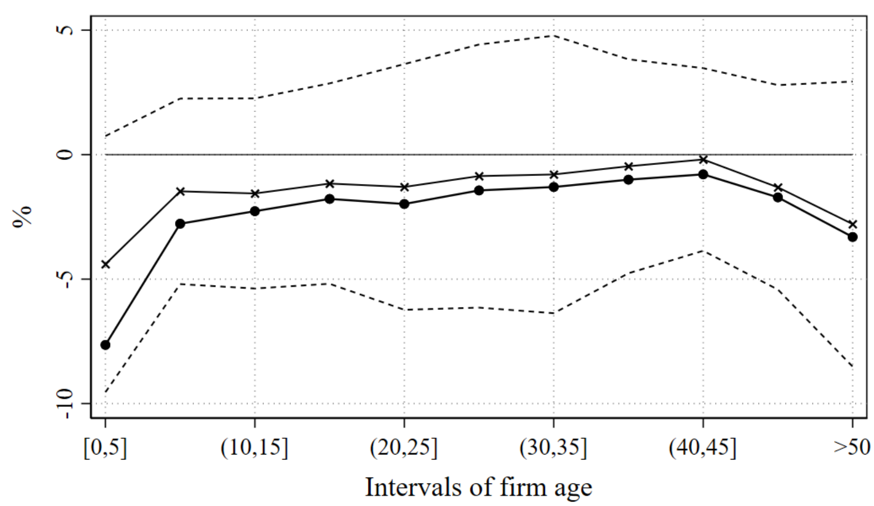
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but excluding observations in which the firm exits by $t + h$.

Figure E.3. Investment response across age groups at $h = 3$, excluding entrants.



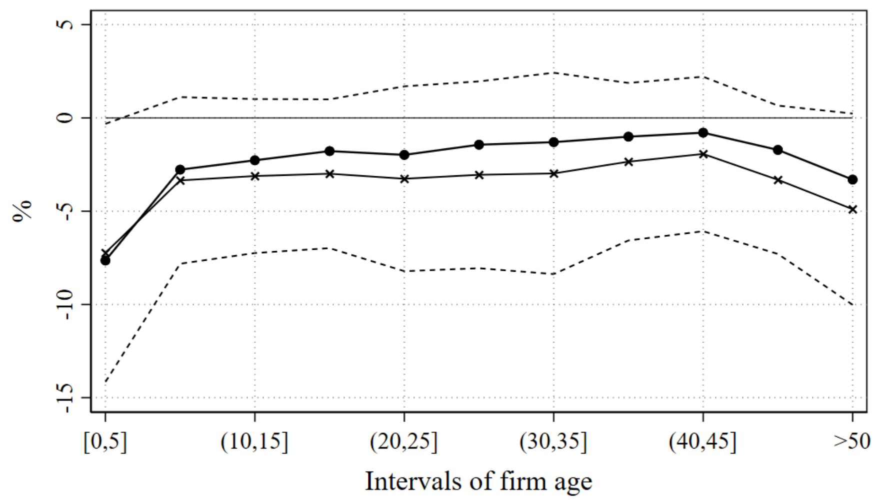
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but excluding observations in which the firm was strictly less than three-years-old at the time of the monetary policy shock, t.

Figure E.4. Investment response across age groups at $h = 3$, controlling for firm size.



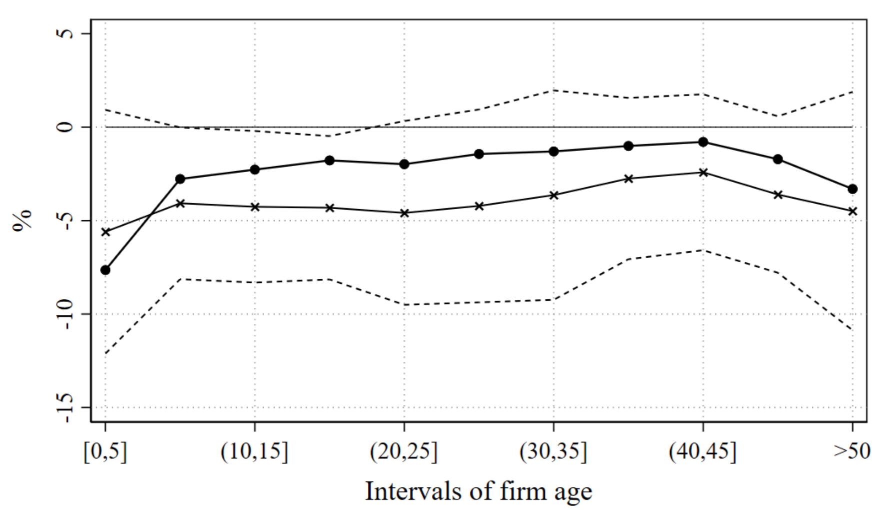
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but including a control for lagged firm size (log of total assets as $t - 1$), and an interaction term between lagged firm size and the monetary policy shock.

Figure E.5. Investment response across age groups at $h = 3$, subsample up to 2011.



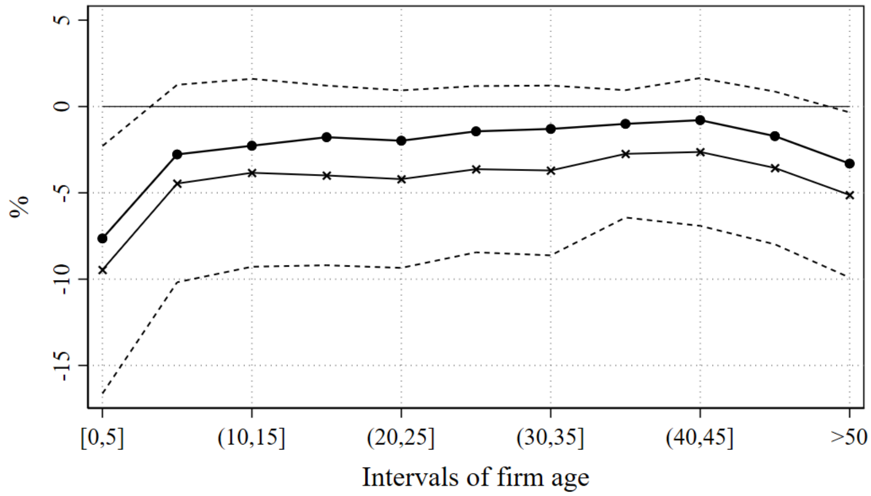
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but only using data up to and including 2011. In 2011, the ECB first departed from its usual policy tools and engaged in unconventional monetary policy. Specifically, in December 2011, the ECB decided on the first set of longer-term refinancing operations for banks with a maturity of up to three years, which was a major departure from previous liquidity allocations.

Figure E.6. Investment response across age groups at $h = 3$, subsample up to 2013.



Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but only using data up to and including 2013. In 2014, concerns emerged that the policy rate might have reached the lower bound. Though this turned out not to be the case, the concern itself might have presented a transmission constraint and can be understood as the first moment where the effective lower bound appeared to hinder policy decisions.

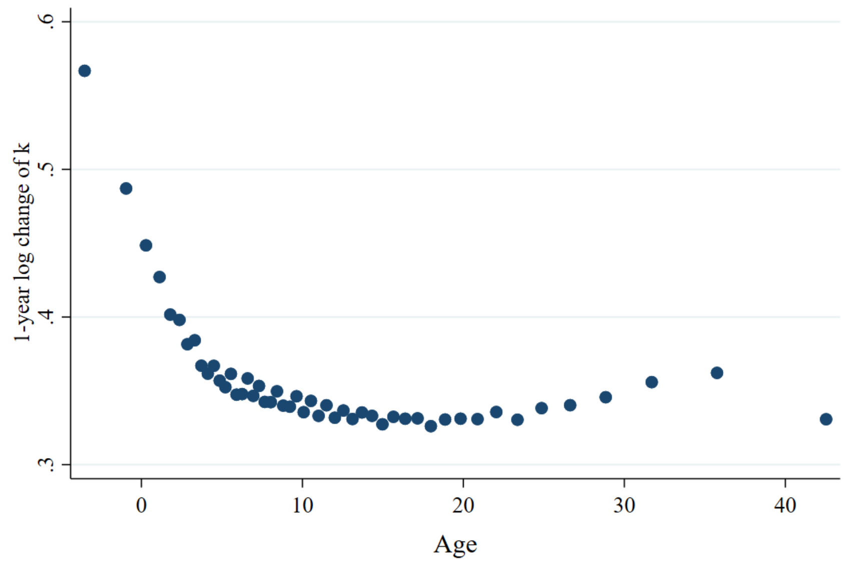
Figure E.7. Investment response across age groups at $h = 3$, controlling for the shadow rate.



Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but controlling for a lagged shadow rate measure (at $t-1$ for the shock at t), which captures what the policy rate would be if there were no lower bound. We follow Hartmann and Smets (2018), and extract a principal component from five shadow rate estimates, namely those by Lemke and Vladu (2017), Kortela (2016), Krippner (2015), and Wu and Xia (2020), using two versions of the rate by Lemke and Vladu (2017).

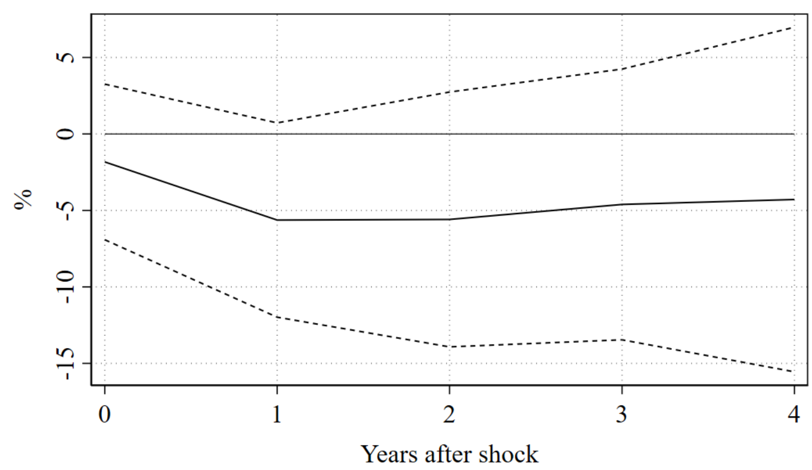
F Additional figures for evidence for mechanisms

Figure F.1. Fixed asset growth by firm age controlling for size.



Note: Median positive growth rates in the stock of fixed assets by firm age from a regression of median positive growth rates on firm age and size. Firm size is the log of total assets in the previous year.

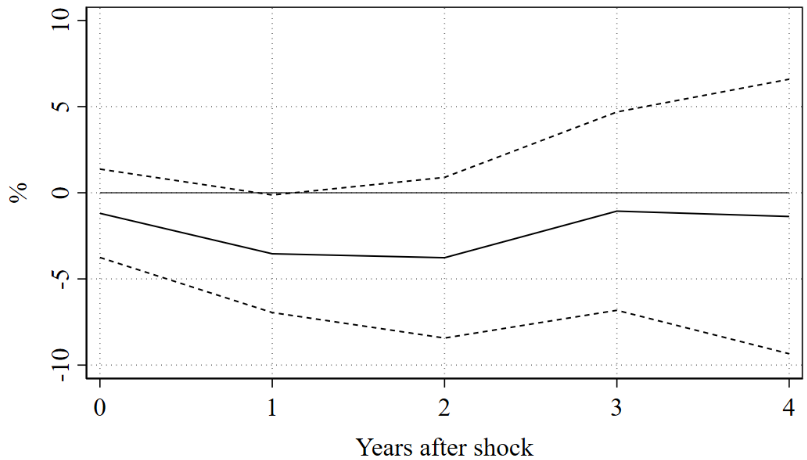
Figure F.2. Average debt response.



Note: The same as Figure 2, except using a horizon of $h = 1$ years after the shock, and using the cumulative change in the log of firms' debts as the outcome variable, rather than in the log of their capital stocks.

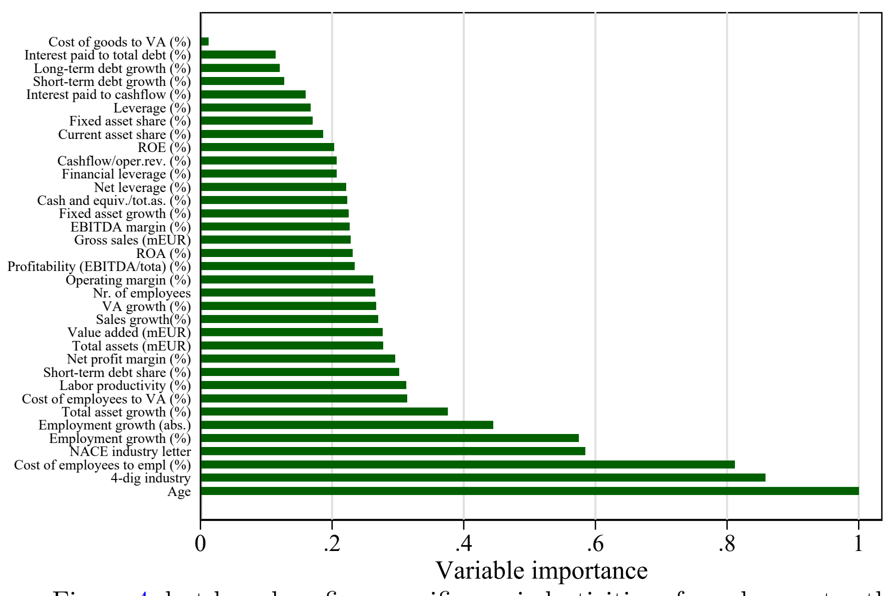
G Findings for employment

Figure G.1. Average employment response.



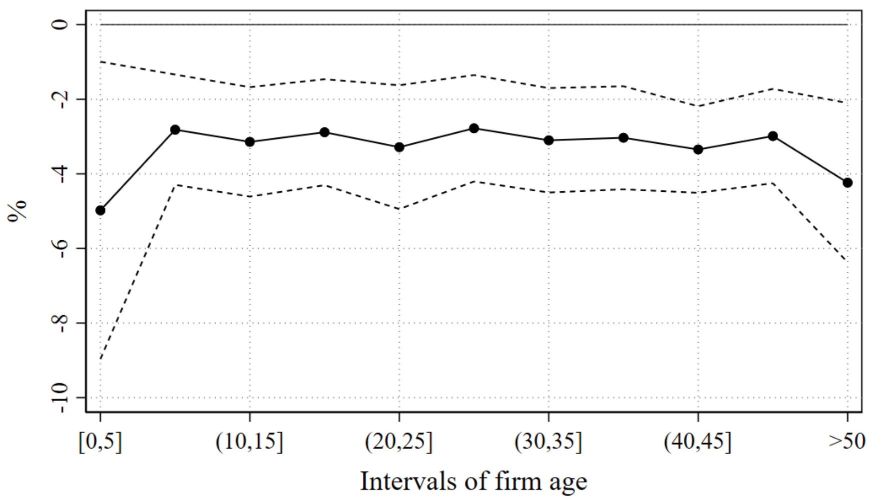
Note: The same as Figure 2, but using the cumulative change in the log of firms' employment as the outcome variable, rather than in the log of firms' capital stocks.

Figure G.2. Predictors of firm-specific employment semi-elasticities.



Note: The same as Figure 4, but based on firm-specific semi-elasticities of employment rather than capital to monetary policy shocks. We use a horizon of $h = 2$ years after the shock rather than $h = 3$ to match the horizon at which the magnitude of the average response peaks for employment (Figure G.1).

Figure G.3. Employment response across age groups at $h = 2$.



Note: The same as Figure 5, but using employment rather than capital semi-elasticities estimated separately for each age interval.