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 capital 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. Based on this result, we estimate age-specific capital semi-elasticities. 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 because they are closer to their optimal scale, and thus less likely to pay the fixed cost. A key implication is that monetary policy is less potent in an economy with older firms.

Keywords: Firm heterogeneity, Monetary policy transmission, 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. The responsiveness to monetary policy declines with age, and is statistically insignificant for older firms. The biggest difference is between the youngest firms (0 to 5 years old) and all older firms. Specifically, three years after a 25 basis point contractionary monetary policy shock (an interest rate increase), the total fixed assets of firms between 0 and 5 years old are seven percent lower than they would be otherwise, whereas the total fixed assets of firms around 40 years old are only one percent lower. It follows that these youngest firms 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 the data, 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 size, which determines its willingness to pay fixed adjustment costs, and is not picked up by other variables in the data. For example, small firms may be young and far from their optimal size, and thus responsive to monetary policy; but they may be unproductive, and so already at their optimal size, and thus not responsive.

We focus on a simple model of a single firm to illustrate the theory. Nonetheless, it makes sharp qualitative predictions for which we find evidence in the data. In the theory, older firms want to invest less as a share of their capital stocks, and as a result, they are less likely to invest at all. In the data, among firms with growing stocks of fixed assets, the growth rate is falling in age. This holds unconditionally, and controlling for firm size or 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 and the aggregate capital stock, 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, monetary policy may be less potent after the recent fall in firm entry and shift toward older firms. Similarly, different firm age distributions across countries can generate different aggregate responses to monetary policy. In particular, in the euro area, where one central bank presides 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 predicts its growth rate unconditionally, but not 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 distance of firms' capital stocks from 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

[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.

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

Outline. In Section 2, we describe the firm-level data. We discuss the identification of monetary policy shocks and the empirical framework 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 lifecycle firm investment model that rationalizes our empirical findings, provide empirical evidence for the model's main predictions, and provide evidence against other potential theories. 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 contains a list of all variables and transformations for the data used throughout 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.1).[5] Moreover, in each country, the sample firm size distribution is close to the overall distribution (see Figure A.1 in Appendix A.1).

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 by the HICP index of the respective country with base year 2015. Firm age is in years. pn denotes the n^{th} percentile.

Table 1 shows selected summary statistics. We highlight two features or our data set. First, the number of observations is large. Balance sheet information, for example total assets, and firm age 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. Second, there are a few large and old firms (one is more than 900 years old[6]), 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.

[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.

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

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 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 by raising the discount rate and reducing 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 economy. If this second channel dominates, then stock prices rise.[9] Figure 1 plots all surprises in the 3-month OIS rate and concurrent changes in the stock market index. We use shocks in the top-left and bottom-right quadrants.

Since firms report only once a year, we match firm-level observations in a given month to the sum of all monetary policy shocks in the previous twelve months. Figure B.1 in Appendix B shows the time series of the shock and its twelve-month moving sum.

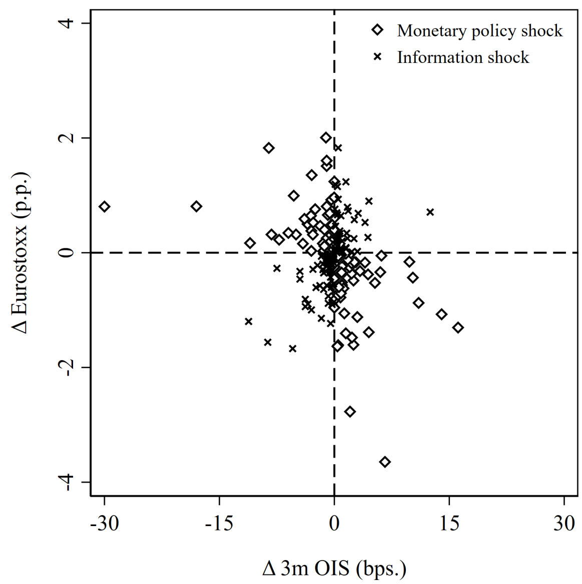
Finally, to examine the plausibility of our identified monetary policy shocks, we estimate impulse response functions for various aggregate variables to an identified shock. Figure B.2

[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: High-frequency changes in the 3-month OIS rate and the Eurostoxx index around meetings of the ECB Governing Council from 1999 to 2018. Surprises in the top-left and bottom-right quadrants are classified as monetary policy shocks, which we use, and the remaining are classified as information shocks, which we do not use. The data are from the Euro Area Monetary Policy Event-Study Database by Altavilla et al. (2019).

in Appendix B 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. Following a contractionary shock, the short-term rate jumps up 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.

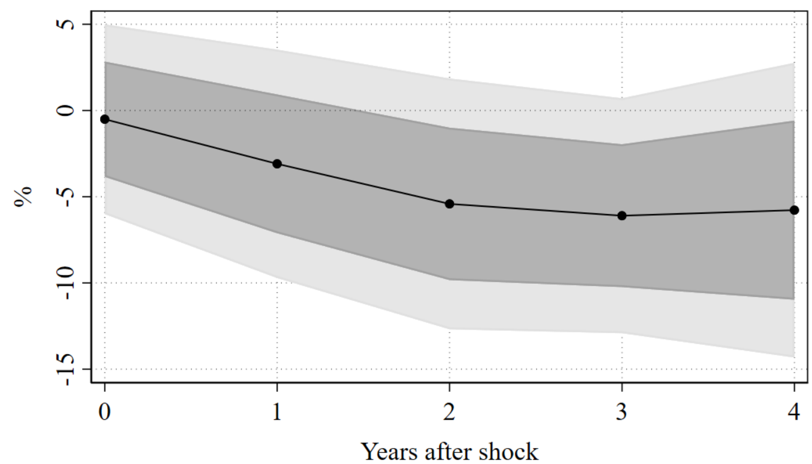
3.2 Homogeneous effects of monetary policy shocks

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 capital 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 shows the 90% (68%) confidence intervals, 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. The response is not statistically significant at the 10% level for any horizon, and is significant at the 30% level only for horizons of 2 years or longer. 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 a separate response to monetary policy shocks for each firm. We use a machine learning algorithm to detect which characteristics best explain differences across firms, and find that firm age is the most important. We then estimate age-group specific responses to monetary policy shocks to understand and quantify the importance of age. In Appendix E, we find similar results using employment rather than capital.

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 to h years after—except the semi-elasticity with respect to the shock, $\beta_{i,h}$, is now firm-specific. We omit macroeconomic controls to keep as much variation as possible.[10]

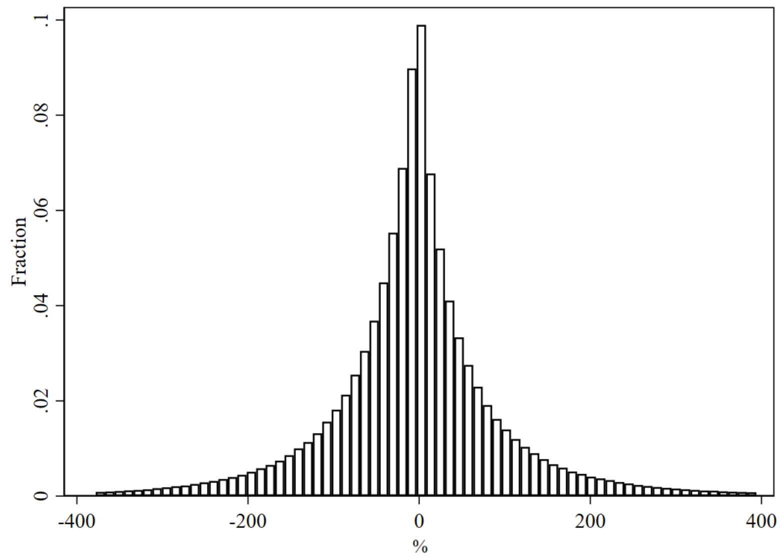
We are interested in the distribution of the estimated semi-elasticities of firms' capital stocks with respect to the monetary policy shock, $\{\hat{\beta}_{i,3}\}$, where we use a horizon of 3 years after the shock to match the timing of the peak of the magnitude of the common response (Figure 2). Figure 3 shows the implied distribution of responses to a 25 basis point increase in the interest rate. The mean is -4.8%, and the median is -4.1%. Many of the estimated responses are large in magnitude, and even positive. This in part reflects that each estimate is relatively noisy since it is obtained from a small number of observations for a single firm. Hence, the distribution should be interpreted with caution. For robustness, we also conduct the following analysis only for firms whose semi-elasticity estimates *(i)* are based on an above-average number of observations and *(ii)* are statistically significant at the 10% level.

4.2 Detecting relevant firm characteristics

We 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), which identifies sample splits along observables that maximize variation in an outcome

[10] We can estimate (2) for around 2 million of the 7.7 million firms in our sample; to have a value for the outcome variable, we can only keep firms with observations over at least five years.

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



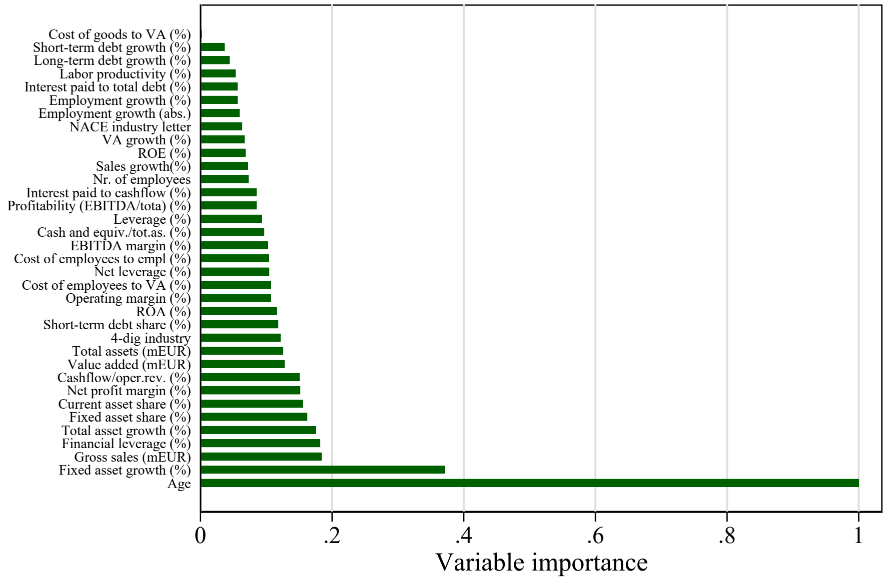
Note: The distribution of percentage responses of firms' capital stocks to a 25 basis point contractionary monetary policy shock, implied by the distribution of semi-elasticities, $\{\hat{\beta}_{i,3}\}$, estimated from equation (2) using a horizon of $h = 3$ years after the shock. The top and bottom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

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 for 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 C.1.

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 (see Appendix C.2 for a full list). To make these variables comparable to the semi-elasticities, we compute their averages over time for each firm.

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 is normalized to one). This "variable importance" is based on how much the predictability of the estimated semi-elasticities declines if a variable is excluded from the analysis. The main 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.

Figure 4. Variable importance of 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 scale of the most important variable is normalized to one. 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, and a detailed list is in Appendix C.2. "VA" denotes value-added.

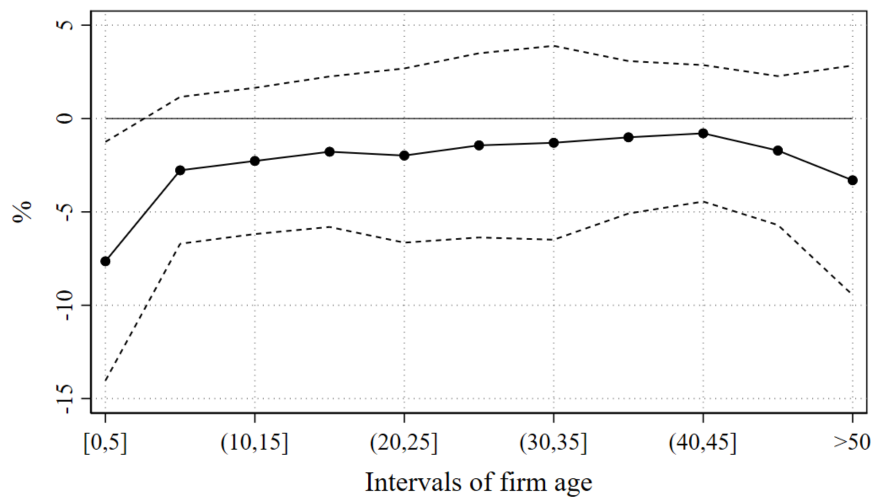
Alternative Random Forest specifications. We conduct three robustness checks, and list the results in Appendix C.3. First, we exclude explanatory variables that are highly correlated with other explanatory variables. The aim is to insure that a low importance for a variable does not simply reflect the presence of other correlated variables. Age remains the most important 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 10% 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. The distributions of semi-elasticticies for the subsamples used in the latter two robustness checks are in Appendix C.3.

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

4.3 Transmission across firm age

Given our findings thus far, we now investigate in detail 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, estimate a single 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] We use a horizon of 3 years after the shock, in line with the rest of our heterogeneous effects analysis.

Figure 5. Capital responses across age groups at $h = 3$.



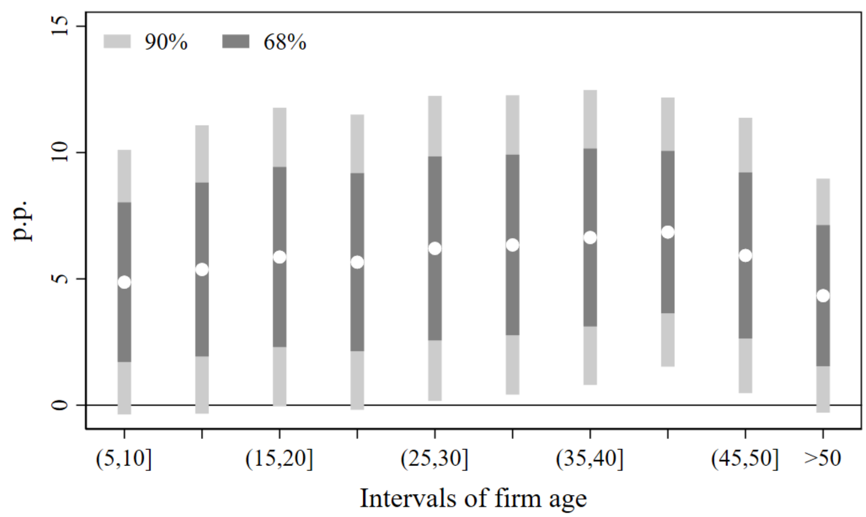
Note: The percentage response of firms' capital stocks to a 25 basis point contractionary monetary policy shock as a function of firm age, implied by semi-elasticities estimated separately for each age group using equation (1) with a horizon of $h = 3$ years after the shock. An observation is grouped based on the firm's age at the time of the monetary policy shock. The dashed lines form the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.

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 main difference is between firms 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 otherwise, whereas capital is 2.7% lower for firms 6 to 10 years old, and is 0.8% lower for firms 40 to 45. Moreover, the response is statistically significant at the 10% level only for the youngest firms. Recall that the single response estimated for all

[12] In Appendix D, 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.

firms in Section 3.2 was not statistically significant at the 10% level. Finally, Figure 6 shows the difference in responses between each age group and the youngest group, which is always statistically significant at the 15% level.

Figure 6. Differences in capital responses across age groups from the youngest group at $h = 3$.



Note: For each age group, the white dot is the difference between that group's response from Figure 5 and the youngest 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.

Alternative specifications. As robustness checks, we run the following variations on our estimation of age group-specific semi-elasticities: excluding exiters or entrants around each monetary policy shock; controlling for lagged firm size (log total assets) and its interaction with the shock; excluding years after 2011 during which the ECB engaged in unconventional monetary policy;[13] controlling for a shadow rate measure of what the interest rate would be absent a lower bound; and excluding years after 2013 during which many speculated that the interest rate was at its lower bound.

The results, shown in Appendix D, are mostly the same as in the baseline estimation; the biggest difference is that excluding exiters or years after 2013 makes the gradient of the response with respect to age much flatter. The former 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.

[13] In December 2011, the ECB first departed from its usual policy tools and engaged in unconventional monetary policy: it 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.

Contribution to the aggregate response across firm age. We compute the share of the aggregate capital response for which each age group is responsible. Specifically, we can write the percentage change in the aggregate capital stock in response to a 25 basis point contractionary monetary policy shock—at a horizon of 3 years after the shock—as the capital stock-weighted average of the responses for each age group:

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

where ΔK is the aggregate response, ω_j is age group j's share of the aggregate capital stock, and Δk_j is the group j response. The weights $\{\omega_j\}$ are their averages over time in our sample. Given the gradient in responses in Figure 5, we consider only five age groups: the same first three groups, firms 16 to 25 years old, 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 otherwise. The youngest firms (0 to 5 years old) account for 35% of this aggregate response, even though their capital accounts for only 11% of the aggregate stock. By contrast, firms older than 25 are responsible for only 22% of the aggregate response, though their capital is 43% of the aggregate stock.

5 Theoretical mechanisms

We now propose a theoretical framework based on capital adjustment costs to rationalize our empirical findings that a firm's age is the most important predictor of its response to monetary policy shocks, and that the response is declining in age. The model illustrates the key 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 proportional to the percentage change, and a fixed cost 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 latter 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:

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

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

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

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, we can 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:

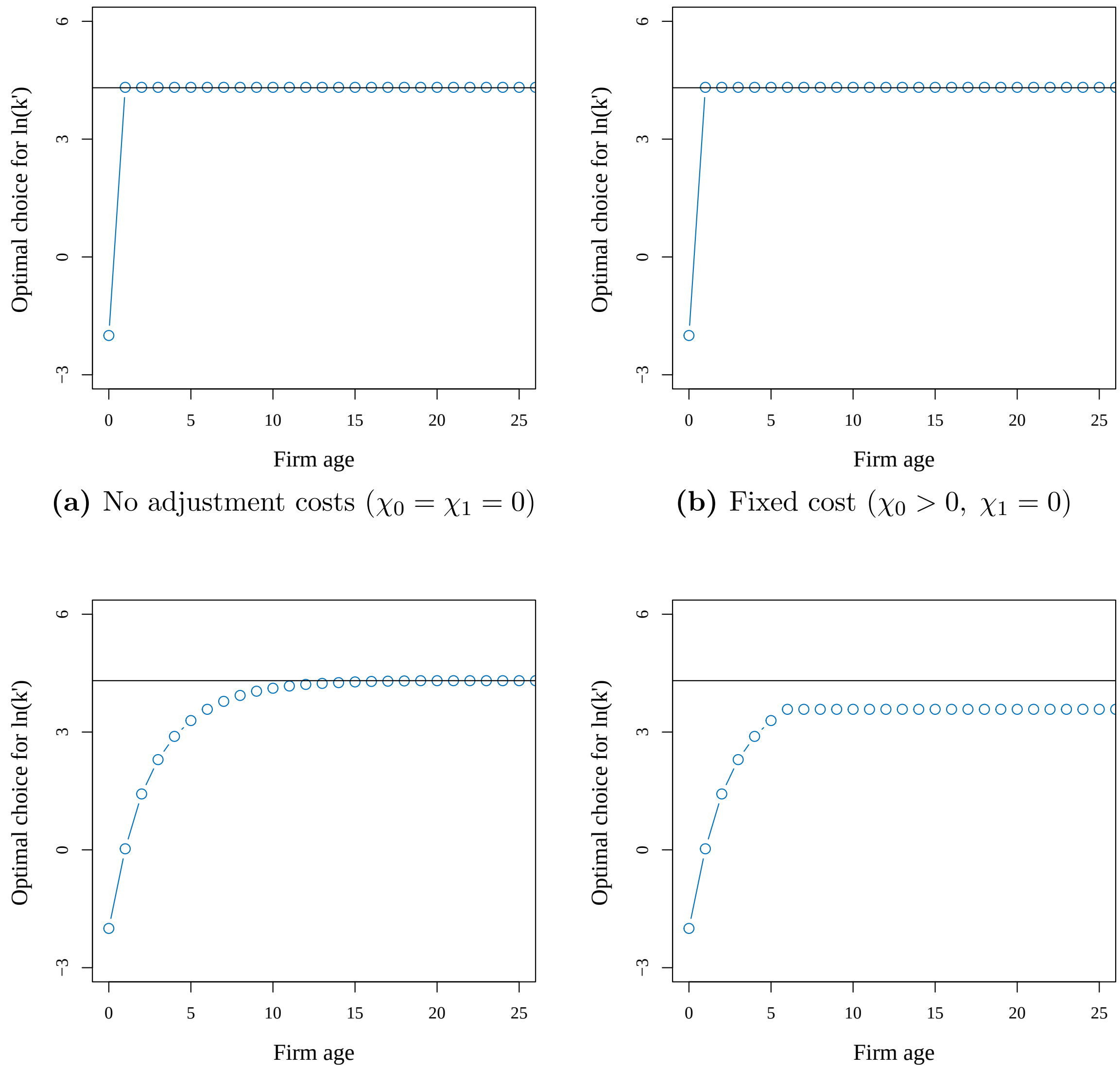
$$V_a(k) = \sup_{k'} \left\{ z(k')^\alpha - rk' - \frac{\chi_1}{2} \left(\frac{k' - k}{k} \right)^2 k + (1+r)^{-1} V(k') \right\}$$

subject to $k' \neq k$; and $V_n(k)$ is the value function conditional on not adjusting:

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

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 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, so the firm does not adjust.

Figure 7. Capital choice across firm age.



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

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

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

(d) All costs ($\chi_0 > 0,\ \chi_1 > 0$)

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 absent adjustment costs, k^*.

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. 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. 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.

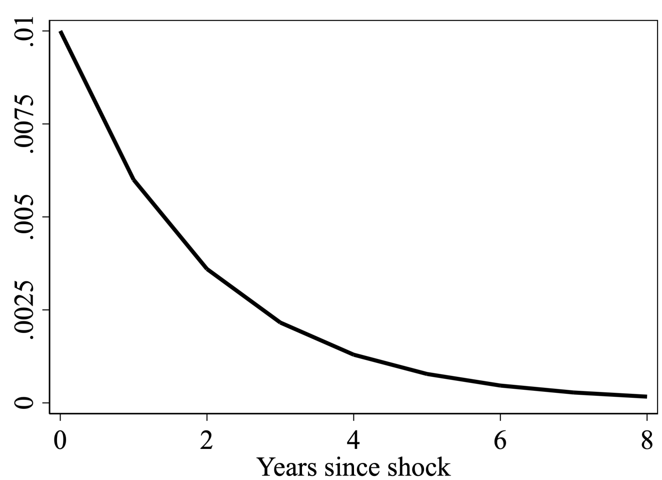
5.2 The effects of an interest rate shock

We now show that the model delivers our finding that younger firms' capital stocks are more responsive to interest rate shocks. The shock occurs at $t = 0$ after which the interest rate is:

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

where $\varepsilon_0 > 0$ is the initial shock and $\rho \in (0, 1)$ its persistence. Figure 8 shows the path of ε_t.

Figure 8. Path of the interest rate shock.



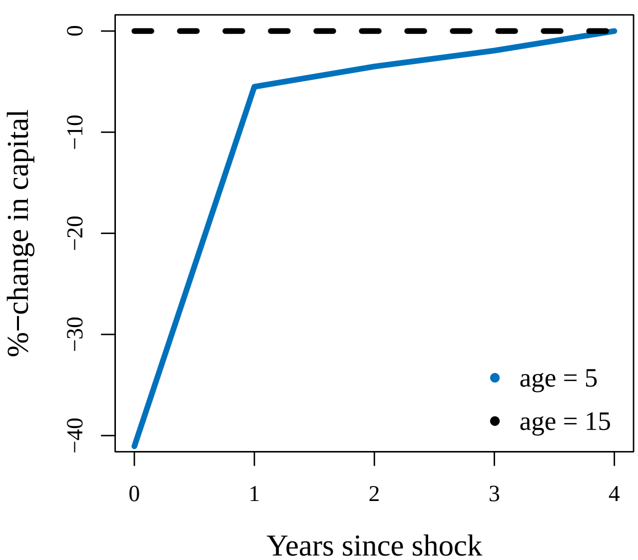
Formally, the firm's value function now solves the Bellman equation:

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

where ε is the current interest rate shock, so $\rho\varepsilon$ is next period's shock. The shock lowers the firm's capital choice given its capital in the previous period. First, it increases the rental rate, which lowers the marginal value of capital for current profits. Second, part of the incentive to invest is to have more capital in the future because the firm is below its optimal size, k^*. The shock increases the discount rate, which lowers the significance of future profits.

Figure 9 shows the impulse response function of capital to the interest rate shock if the firm is young when the shock hits, and if it is old when the shock hits. The young firm's capital is immediately lower than it would be absent 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 firm's age determines the distance between its capital and the optimal level k^*, and so whether it is paying its fixed adjustment cost absent the shock. Moreover, the shock is small and temporary, so it affects the decision to pay the fixed cost for only a small set of firm ages. Thus, the young firm responds because it is far from its optimal size, whereas the old firm does not respond because it is close to its optimal size.

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



Note: The percentage change in the firm's capital from its path without the shock, for two firm ages computed when the shock occurred. There are fixed and convex adjustment costs ($\chi_0 > 0$, $\chi_1 > 0$).

Age vs. size. Our Random Forest algorithm found that for predicting a firm's response to monetary policy shocks, age is much more significant than size. Moreover, our estimated age group-specific semi-elasticities are mostly the same whether or not we control for lagged firm size and its interaction with the shock. However, in the model, there is an exact relationship between firm age and size, so there is no distinction between the two. Nonetheless, we argue that our mechanism speaks more to the importance of age than of size.

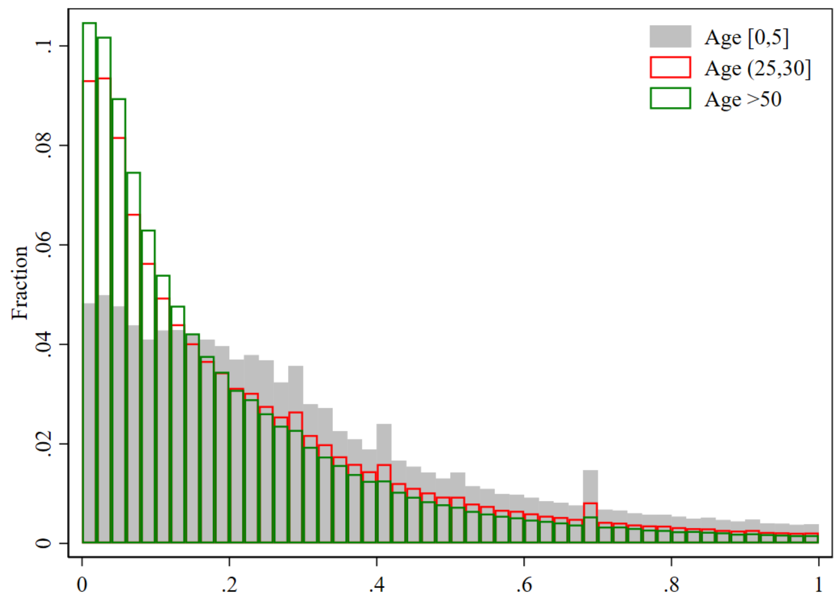
Specifically, we can break the equivalence between age and size by extending the model to a distribution of firms with different values of permanent productivity, z. As in the baseline model, a firm grows over time toward its optimal size. A firm's responsiveness to interest rate shocks depends on the 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. 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 pay their fixed costs and adjust their capital stocks absent the monetary policy shock. This is crucial because it makes them more responsive to monetary policy shocks. From 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 and firms older than 50, as was the case in Figures 5 and 6 on the responsiveness of firms to monetary policy shocks.

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



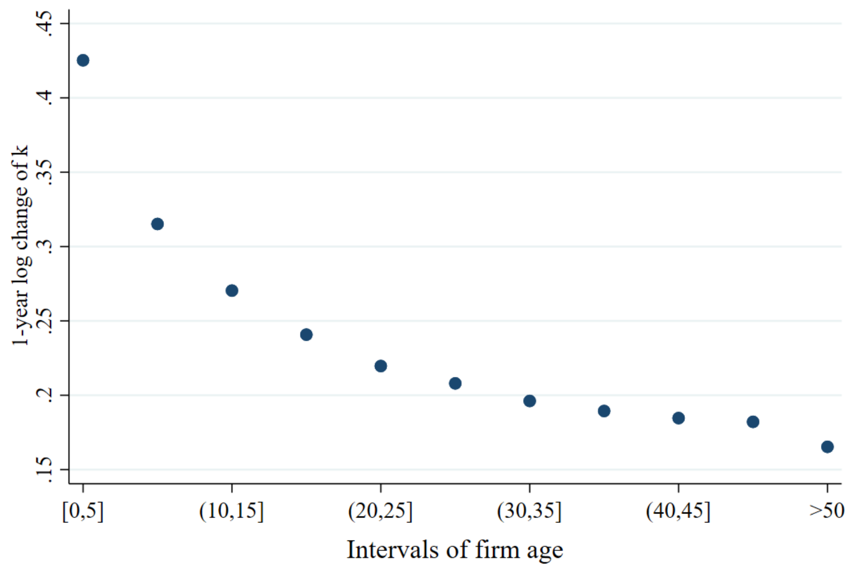
Note: The distribution of absolute values of annual total fixed asset growth rates for different firm age groups. The x-axis is the absolute value of the change in fixed assets relative to fixed assets in the previous year. The y-axis is the fraction of firms in each of fifty bins; values greater than 1 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. From 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 monetary policy shocks, the biggest change is between firms 0 to 5 years old and all older firms. Finally, the pattern holds when *(i)* controlling for firm size and *(ii)* considering within-firm variation by controlling for firm fixed effects. This is in line with the finding in Haltiwanger et al. (2013) that younger firms tend to grow faster, unconditionally and controlling for firm size.

5.4 Alternative mechanism: financial frictions

Our proposed theory relies solely on capital adjustment frictions. In the literature, the most prominent theory for monetary policy transmission heterogeneity across firms relates

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



Note: Median annual growth rates in fixed assets by firm age, among positive growth rates.

to financial frictions.[14] The idea is that monetary policy shocks affect borrowing costs and the value of collateral firms use to obtain funding. This generates 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.

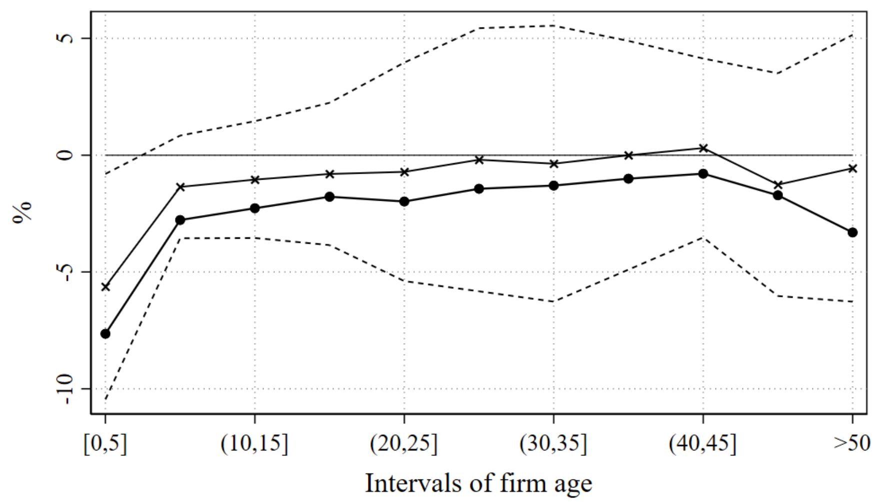
We now provide evidence against financial frictions as an explanation for our empirical results. First, our Random Forest algorithm found that for predicting a firm's response to monetary policy shocks, various measures of its financial position are much less important than its age. Thus, the importance of firm age holds when controlling for these financial measures. Moreover, the heterogeneity in responses to monetary policy across firms driven by financial frictions is less significant than the heterogeneity driven by firm age.

Second, we show that our estimated age group-specific responses to monetary policy shocks are nearly the same if we control for measures of firms' financial constraints. If financial frictions explain our results, then these controls should weaken the importance of firm age. Specifically, 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 and its interaction with the shock.

[14] For example, Gertler and Gilchrist (1994), Jeenas (2019), Ottonello and Winberry (2020), Cloyne et al. (2022) and Durante et al. (2022).

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,[15] 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 contractionary monetary policy shock by firm age. The patterns are mostly unchanged from our baseline results, in particular the differences in responses between the youngest firms and all older firms.

Figure 12. Capital responses across age groups, controlling for debt-to-assets ratios.

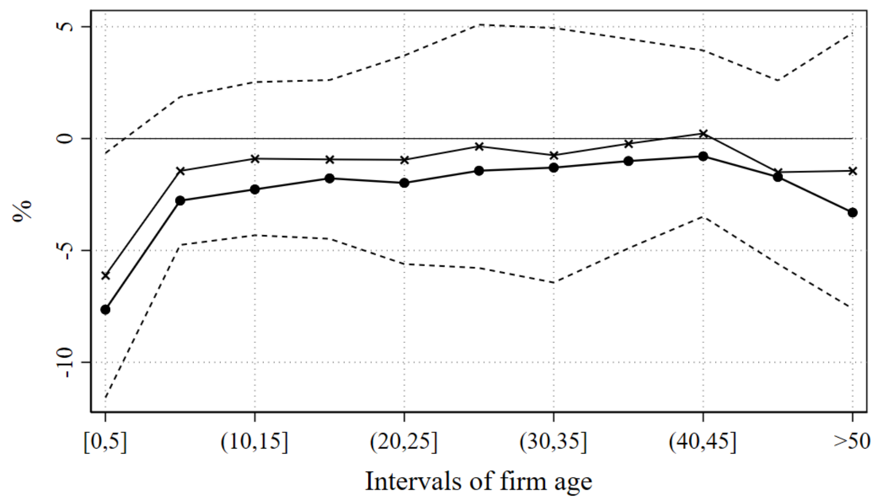


Note: The percentage response of firms' capital stocks to a 25 basis point contractionary monetary policy shock as a function of firm age, implied by semi-elasticities estimated separately for each age group using equation (1) with a horizon of $h = 3$ years after the shock. An observation is grouped based on the firm's age at the time of the monetary policy shock. The line with dots is the baseline (Figure 5); the line with x-markers is controlling for a firm's ratio of total debt to total assets in $t-1$ (the shock is at t) and its interaction with the shock at t. The dashed lines form the 90% confidence intervals for the latter case, based on two-way clustered standard errors by firm and year-month.

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 firm owner's private home as collateral, and that housing values are particularly sensitive to monetary policy. If this makes younger firms' capital more responsive than older firms' to monetary policy shocks, then we should see the same pattern for the responsiveness of firms' debts; collateral matters because it affects how much a firm can borrow. Thus, to test whether it explains our empirical results, we

[15] Lian and Ma (2020) and Drechsel (2023) argue that cashflow-based constraints are important.

Figure 13. Capital responses across age groups, controlling for debt-to-EBITDA ratios.



Note: The percentage response of firms' capital stocks to a 25 basis point contractionary monetary policy shock as a function of firm age, implied by semi-elasticities estimated separately for each age group using equation (1) with 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. The line with dots is the baseline (Figure 5); the line with x-markers is controlling for a firm's ratio of total debt to EBITDA in $t-1$ (the shock is at t) and its interaction with the shock at t. The dashed lines form the 90% confidence intervals for the latter case, based on two-way clustered standard errors by firm and year-month.

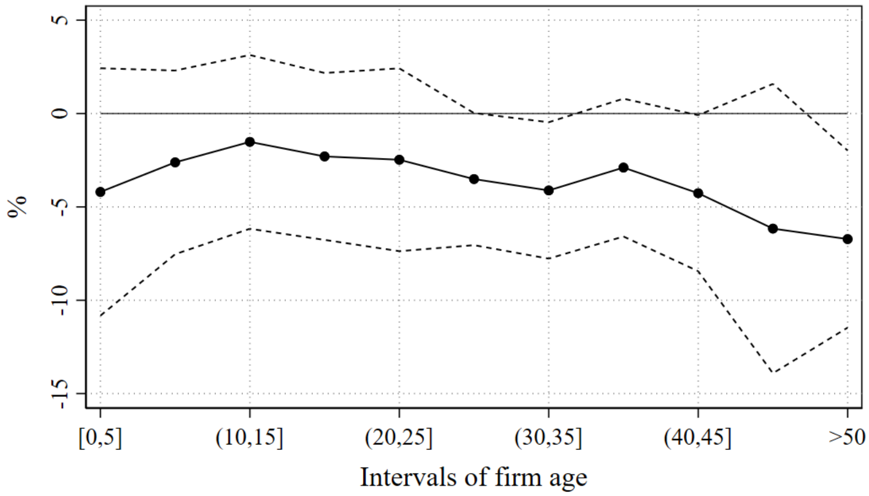
estimate age group-specific semi-elasticities of firms' total debt with respect to monetary policy shocks.[16] Figures 14 and 15 show the implied response of firms' debts to a 25 basis point contractionary monetary policy shock across age groups, and the difference in each group's response from the youngest 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. Moreover, none of the differences are statistically significant at the 10% level, and only the difference for 10 to 15 year old firms is significant at even the 20% level. For firms' capital stocks (Figure 6), the difference in each group's response from the youngest group's was statistically significant at the 15% level.

6 Conclusion

We use machine learning techniques to detect firm age as the most important driver of heterogeneity across firms in their responses to monetary policy shocks. Building on this

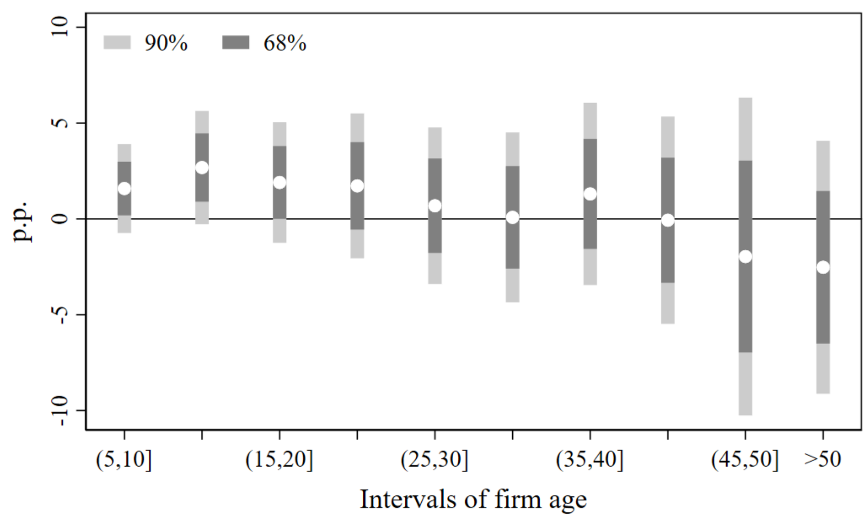
[16] We use a horizon of $h = 1$ year after the shock because if we estimate one semi-elasticity for all firms, then its magnitude peaks after 1 year (Figure D.8 in Appendix D).

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



Note: The percentage response of firms' total debt to a 25 basis point contractionary monetary policy shock as a function of firm age, implied by semi-elasticities estimated separately for each age group using equation (1) with a horizon of $h = 1$ years after the shock. The outcome variable is the cumulative change in the log of firms' debts rather than of their capital stocks (Figure 5). An observation is grouped based on the firm's age at the time of the monetary policy shock. The dashed lines form the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.

Figure 15. Differences in debt responses across age groups from the youngest group at $h = 1$.



Note: For each age group, the white dot is the difference between that group's response from Figure 14 and the youngest 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.

result, age-specific regressions show that younger firms are much more sensitive than older firms to monetary policy. We rationalize our findings in a simple model with fixed and convex capital adjustment costs. Intuitively, younger firms are still growing, and so paying their fixed costs regardless of monetary policy. Thus, they are ready to respond to shocks. Older firms are not paying their fixed adjustment costs, and so do not respond.

Our findings are informative for policymakers: differences in the firm age distribution can generate differences in aggregate monetary policy transmission across countries or over time. In the euro area, where one central bank presides over many countries, this implies that transmission is stronger to countries with a larger share of young firms. Moreover, monetary policy may be less potent after the recent fall in firm entry and shift toward older firms.[17]

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.

[17] This shift holds in our data, shown in Figures A.2 and A.3 in Appendix A.2.

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Appendices

A Data details

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 between 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*)

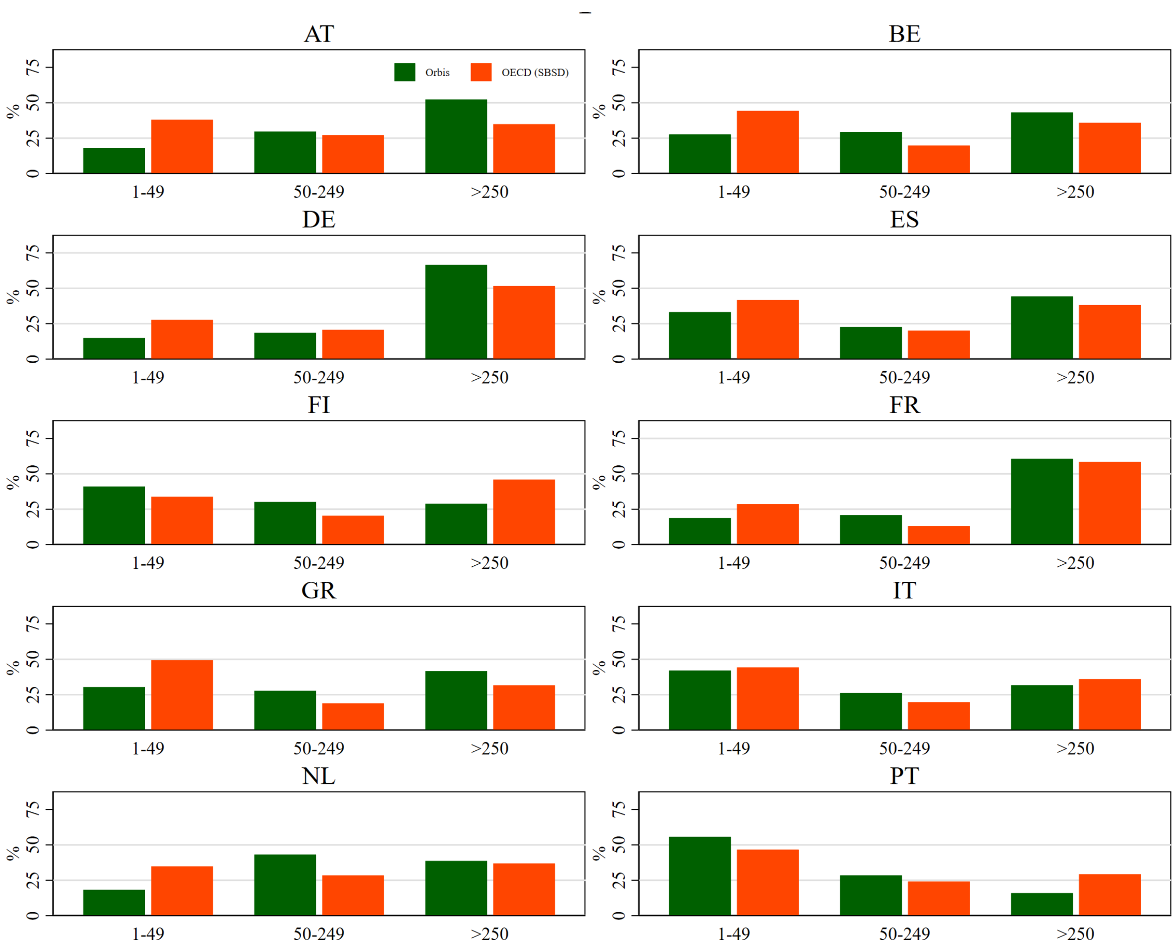
Note: The data identifiers are given in parentheses. A "?" in the identifier is to be replaced with the two-letter country code. All firm-level observations have been deflated with the monthly HICP index for the respective country, where the base year is 2015. In addition, they are winsorized at the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

A.1 Coverage and representativeness

We follow Kalemli-Özcan et al. (2019) (see Table 1 in their paper for coverage, Table 2 for representativeness, and Appendix C for further details). We compare our sample to the aggregate economy based on "Gross output". 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 largest set of non-financial firms, "Business economy, except financial and insurance", which includes firms from sectors with NACE letters B to N, excluding K (finance and insurance). For the comparison, we restrict our firm-level data to these sectors. For representativeness, we further restrict our sample to firm-year observations with values for the number of employees.

For representativeness (Figure A.1) by country in 2017, we compare the share of gross output produced by firms of different sizes in our sample to the OECD data. For coverage (Table A.2) by country and year, we compare gross output in our sample to the OECD data.

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



Note: Comparison along the Orbis variable "Operating revenue" vs. OECD SBSD variable "Turnover" by country in 2017. A bar is the share of gross output by firms in a size bin, which is based on number of employees. In the Orbis data, we restrict the sectors to match those of the OECD SBSD data (NACE letters B to N, excluding K) and we exclude firm-year observations where the number of employees is unavailable.

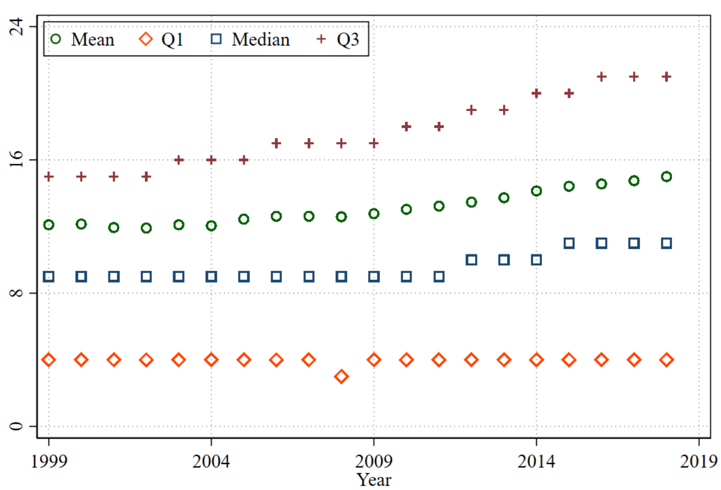
Table A.2: Coverage of the aggregate business economy based on gross output.

	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" vs. OECD SBSD variable "Turnover" by country and year. In the Orbis data, we restrict the sectors to match those of the OECD SBSD data (NACE letters B to N, excluding K). The set of available years is limited by the OECD SBSD data.

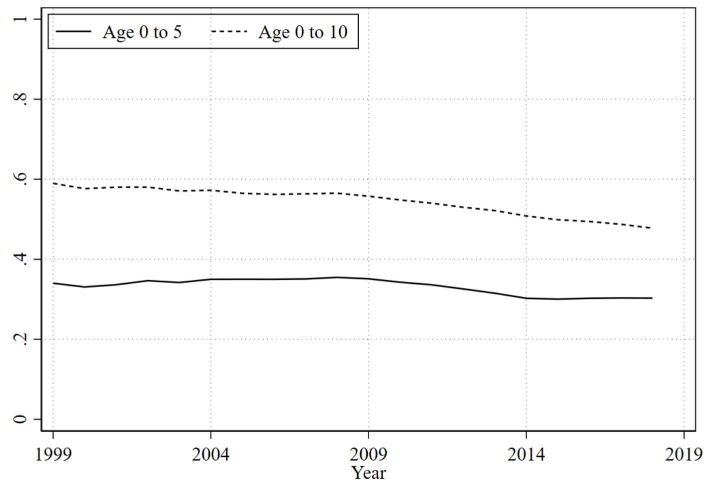
A.2 Additional figures

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



Note: Mean, first quartile, median, and third quartile of the firm-age distribution in the sample over time.

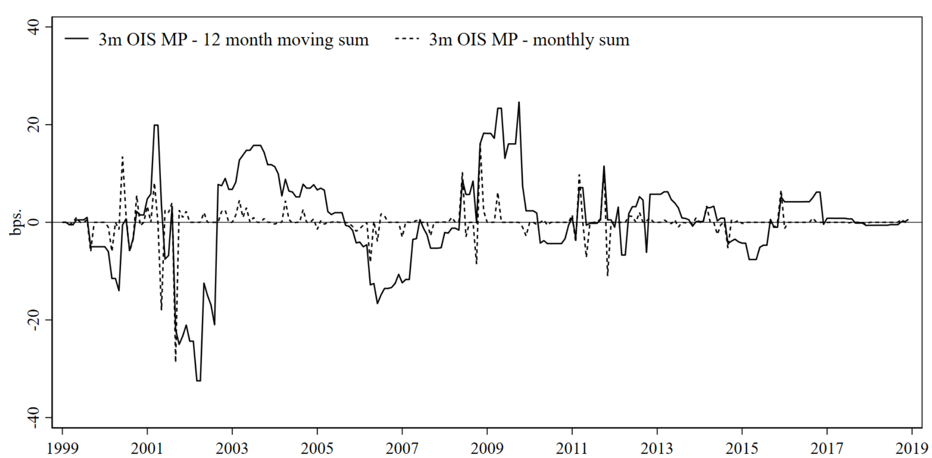
Figure A.3. Share of young firms over time.



Note: The share of sample observations from young firms over time.

B Identified monetary policy shocks

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



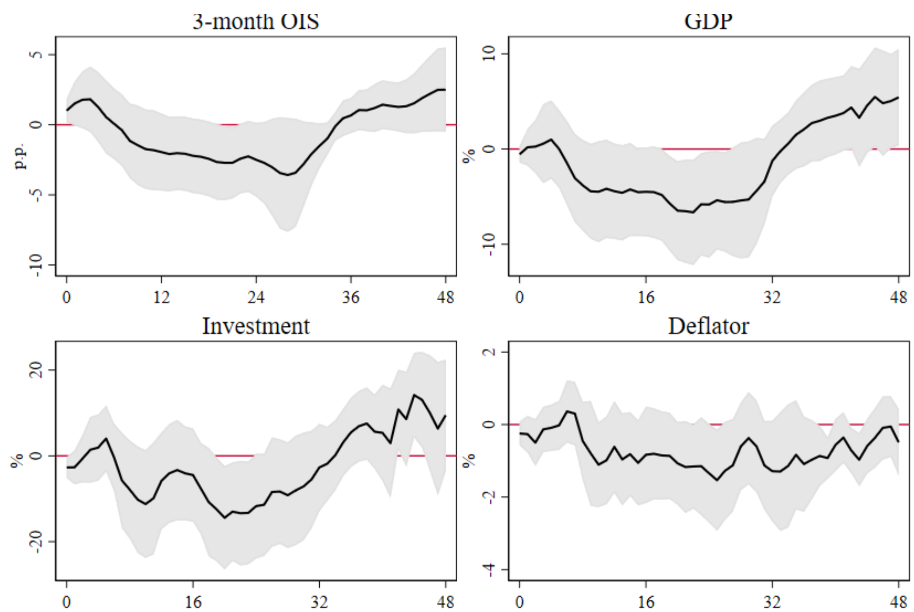
Note: The time series of the identified monetary policy shock and the sum of the past 12 observations.

We estimate local projections (Jordà, 2005) of aggregate variables in response to our identified monetary policy shocks, on a panel of the ten euro area countries that are represented in our firm-level data. The estimation equation is

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

where j denotes country, t denotes year-month, and h is the projection horizon in months. The outcome variables are changes between $t-1$ and $t+h$ in the three month OIS rate (the same in all countries), log GDP, log investment, and the log of the GDP deflator. $\alpha_{j,h}$ is a country fixed effect, and X_{t-1} is a set of common controls: euro area GDP, the GDP deflator, interest rates, and lags of the shock. We compute standard errors using the Driscoll and Kraay (1998) method. The OIS rate is the monthly average of daily observations. GDP, investment, and the deflator are interpolated from a quarterly frequency to a monthly frequency using the Chow and Lin (1971) method; the monthly series for the interpolation are industrial production, construction, and the HICP index for GDP, investment, and the deflator, respectively. Figure B.2 shows the implied responses to a contractionary shock.

Figure B.2. Aggregate impulse responses.



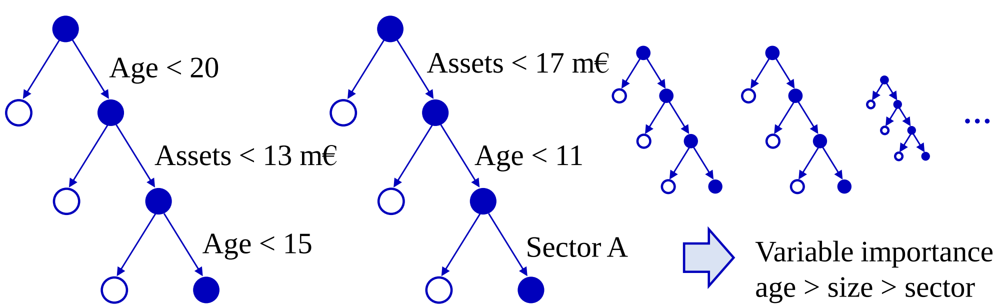
Note: The response of aggregates to a contractionary identified monetary policy shock—implied by our local projection estimates—that generates a 100 basis point increase in the 3-month OIS rate on impact. The x-axis is months after the shock. The gray areas are 90% confidence intervals.

C Random Forest

C.1 Illustrative example of the algorithm

We present a stylized example of the Random Forest algorithm. Figure C.1 shows a hypothetical sketch of the procedure. Y_i is the outcome variable for firm i, and there are three explanatory varaibles, $X_i = \{size, age, sector\}$. The algorithm draws various samples with replacement from the full data set. For each, it assesses multiple times at which 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 split is endogenously determined. The procedure is continued along the respective subsamples obtained from splitting the initial draw 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 random samples, and together they constitute a forest. Across all trees, the algorithm summarizes the relative importance of each explanatory variable for creating variation in the outcome variable. This "variable importance" is normalized to one for the most important variable, and for others is expressed relative to the most important variable.

Figure C.1. Stylized example of the Random Forest algorithm.

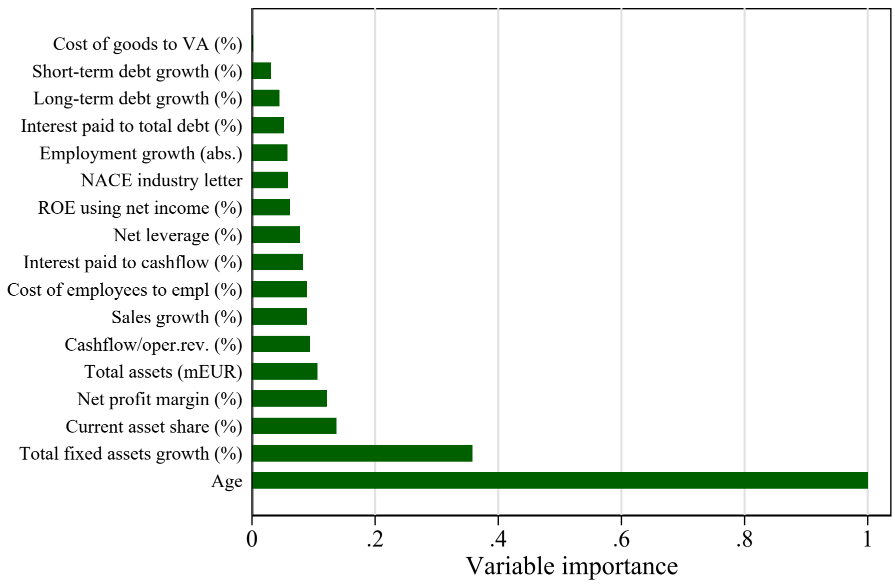


C.2 List of explanatory variables

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 and liquidity:** cash and equivalents/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/number of employees, wage bill/number of employees, wage bill/value added, cost of goods/value added. **Growth (year-over-year):** total assets, employment (also in absolute value), gross sales, value added, fixed assets.

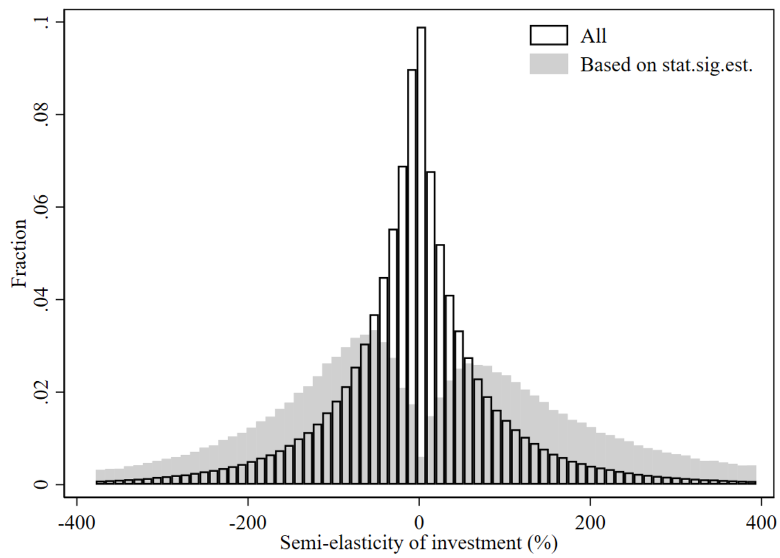
C.3 Alternative subsamples and covariates

Figure C.2. Variable importance using a smaller set of explanatory variables.



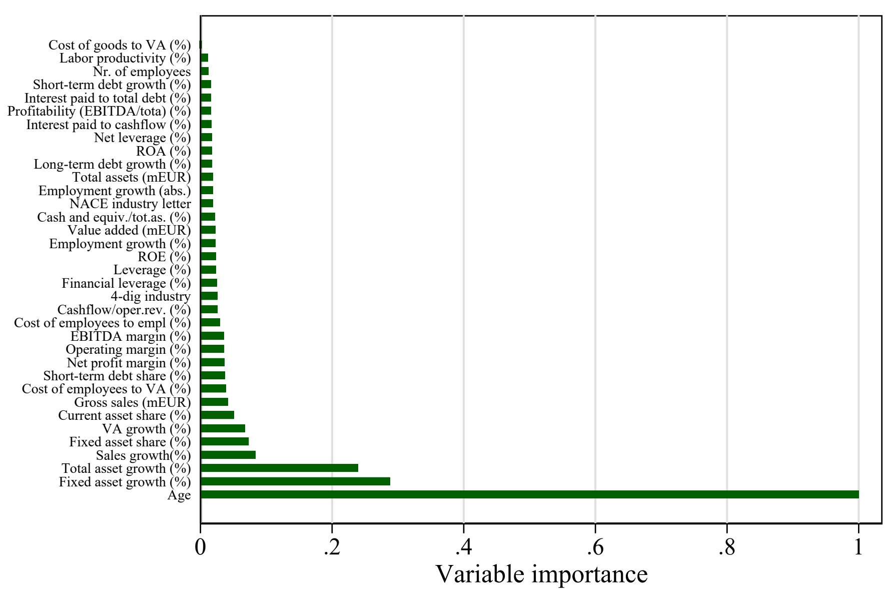
Note: The same as Figure 4, but using a smaller set of explanatory variables.

Figure C.3. Firm-specific capital responses for firms with statistically significant semi-elasticities.



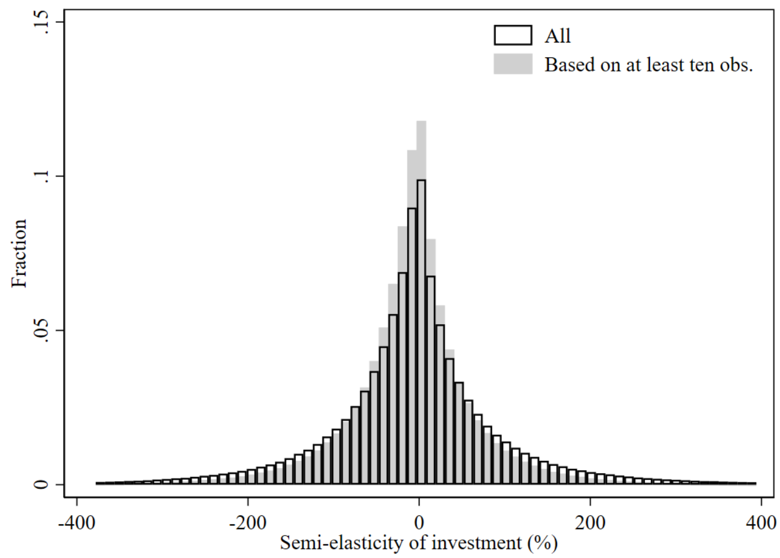
Note: The transparent bars are the same as Figure 3. The gray bars are the same, but only using the subsample of semi-elasticities that are statistically significant at the 10% level.

Figure C.4. Variable importance using firms with statistically significant semi-elasticities.



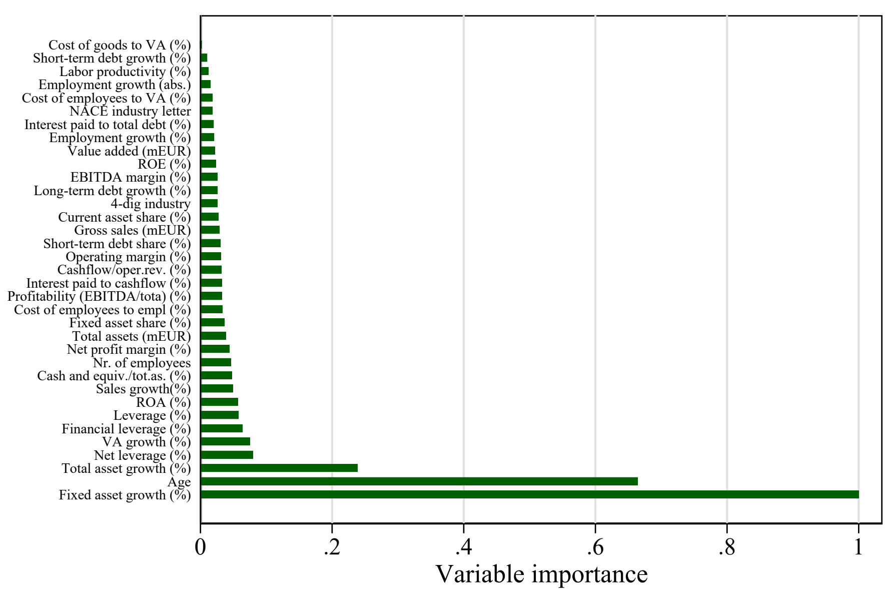
Note: The same as Figure 4, but only using firms with semi-elasticities that are statistically significant at the 10% level.

Figure C.5. Firm-specific capital responses for 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.

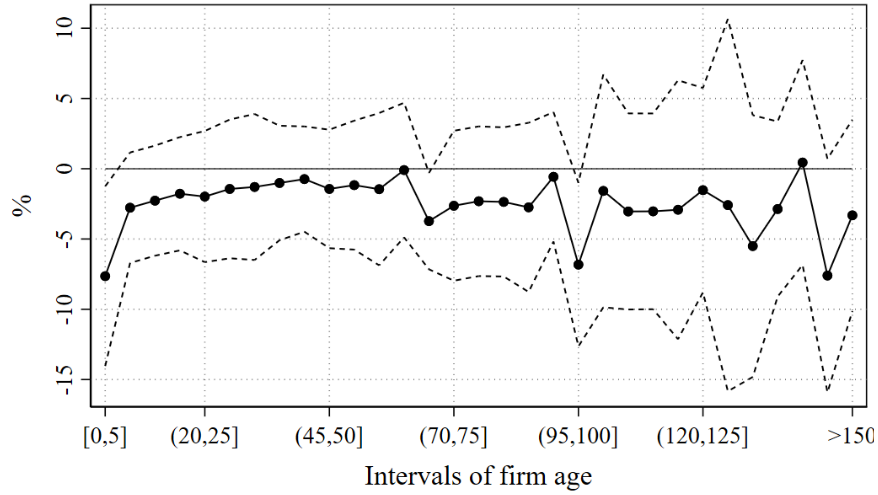
Figure C.6. Variable importance using firms with semi-elasticities estimated from at least ten observations.



Note: The same as Figure 4, but only using firms with semi-elasticities estimated from at least ten observations.

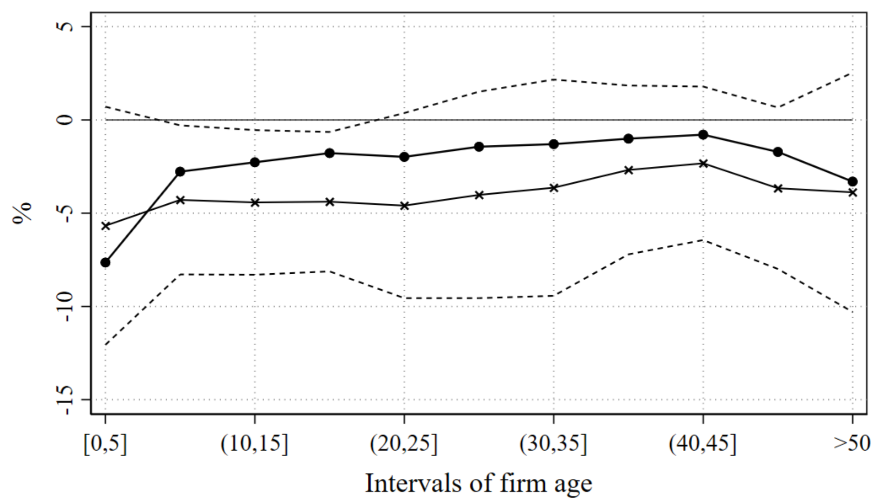
D Additional figures

Figure D.1. Capital responses across age groups at $h = 3$, extended to age 150.



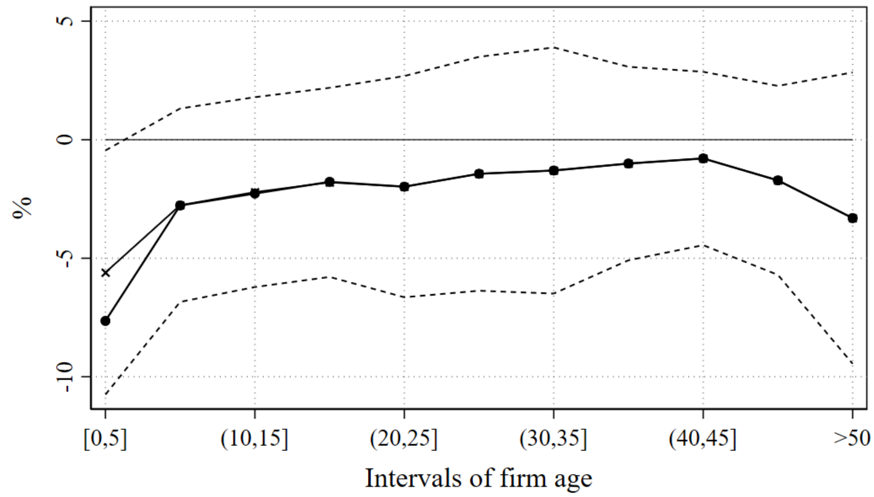
Note: The same as Figure 5, but with the oldest age group split into five year intervals up to age one-hundred-fifty, and then a final group for all firms older than one-hundred-fifty. The dashed lines form the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.

Figure D.2. Capital responses across age groups at $h = 3$, excluding exiting firms.



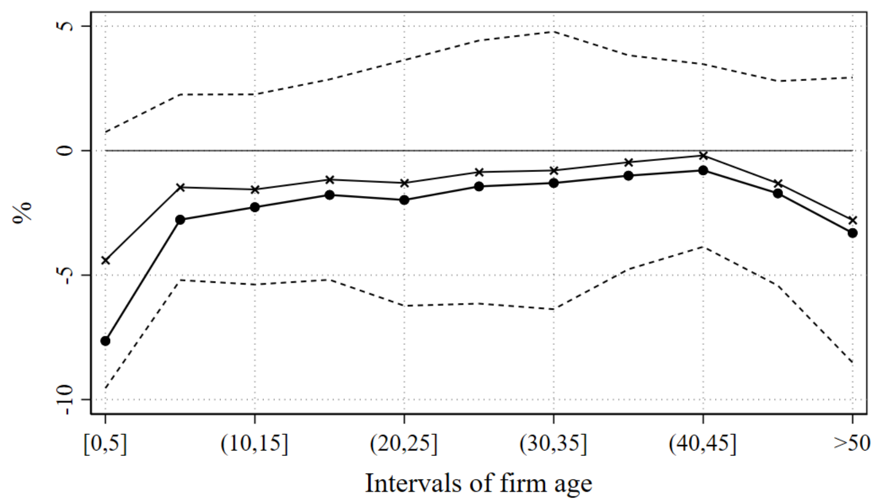
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but excluding observations in which the firm exits by $t + h$. The dashed lines form the 90% confidence intervals for the estimation excluding exiters, based on two-way clustered standard errors by firm and year-month.

Figure D.3. Capital responses across age groups at $h = 3$, excluding entrants.



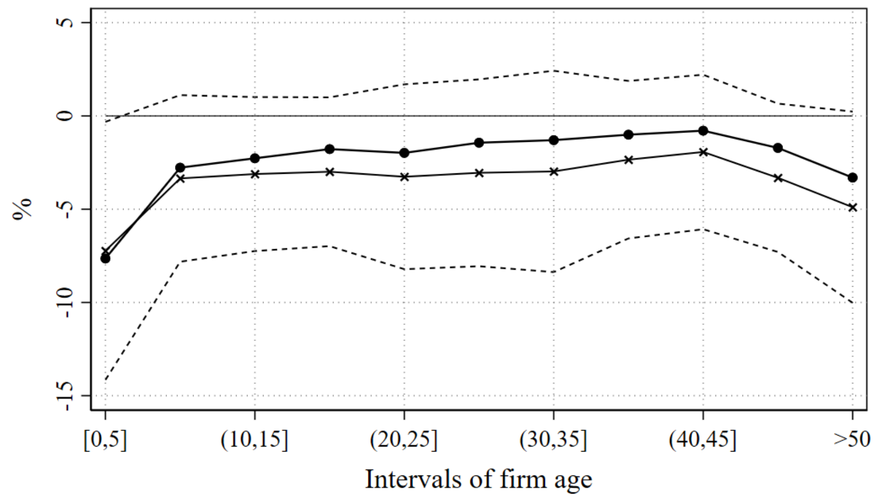
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but excluding observations in which the firm was strictly less than three-years-old at the time of the monetary policy shock, t. The dashed lines form the 90% confidence intervals for the estimation excluding entrants, based on two-way clustered standard errors by firm and year-month.

Figure D.4. Capital responses across age groups at $h = 3$, controlling for firm size.



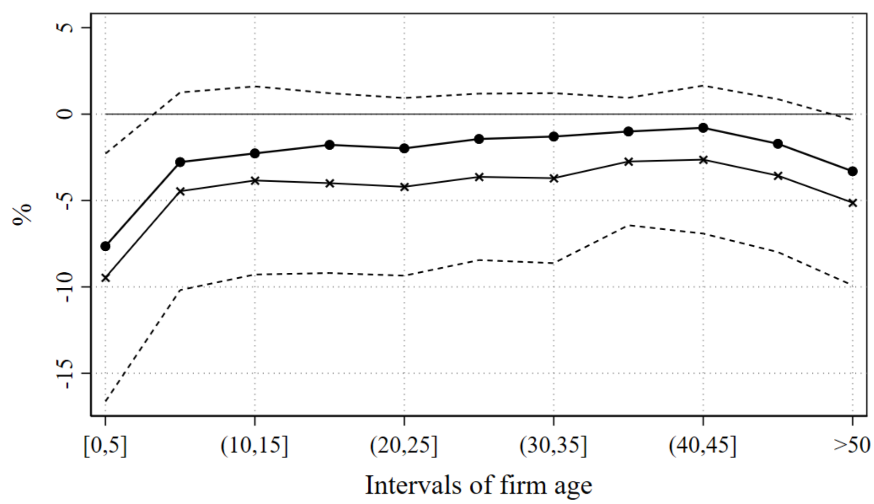
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but including a control for lagged firm size (log total assets as $t-1$) and its interaction with the monetary policy shock. The dashed lines form the 90% confidence intervals for the estimation controlling for size, based on two-way clustered standard errors by firm and year-month.

Figure D.5. Capital responses across age groups at $h = 3$, using years up to 2011.



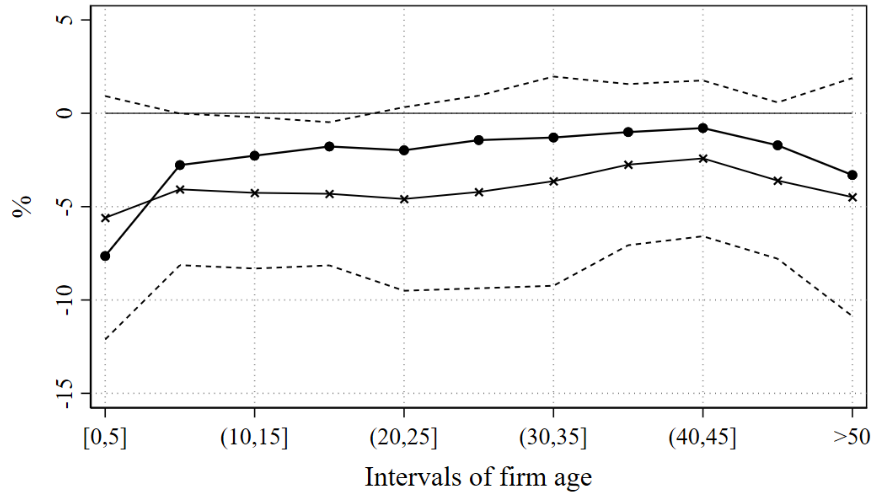
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but only using data up to and including 2011. The dashed lines form the 90% confidence intervals for the estimation using years up to 2011, based on two-way clustered standard errors by firm and year-month.

Figure D.6. Capital responses across age groups at $h = 3$, controlling for the shadow rate.



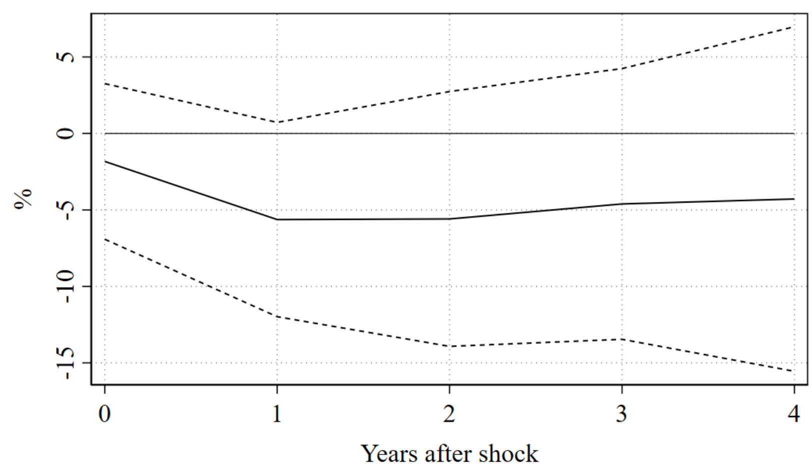
Note: The solid line with dots is from Figure 5. The solid line with x-markers is the same, but controlling for a lagged shadow rate measure (at $t-1$), which captures what the policy rate would be absent a lower bound. Following Hartmann and Smets (2018), we extract a principal component from five shadow rate estimates by Lemke and Vladu (2017), Kortela (2016), Krippner (2015), and Wu and Xia (2020), using two versions of the rate in Lemke and Vladu (2017). The dashed lines form the 90% confidence intervals for the estimation controlling for the shadow rate, based on two-way clustered standard errors by firm and year-month.

Figure D.7. Capital responses across age groups at $h = 3$, using years 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. The dashed lines form the 90% confidence intervals for the estimation using years up to 2013, based on two-way clustered standard errors by firm and year-month.

Figure D.8. Average debt response.

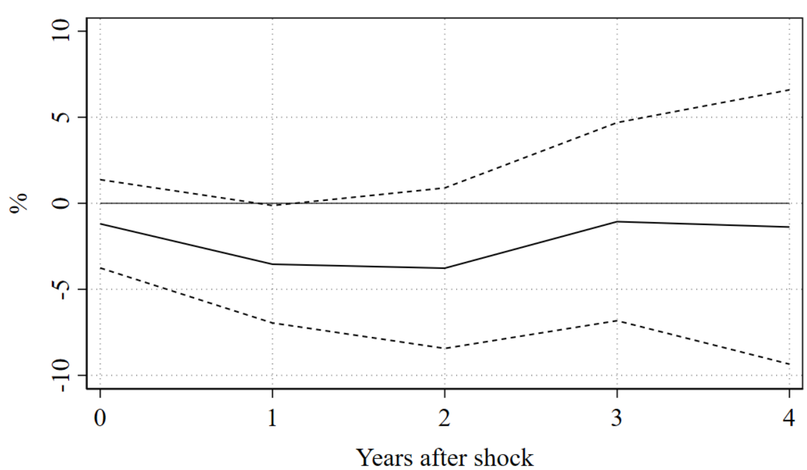


Note: The percentage response of firms' total debt to a 25 basis point contractionary monetary policy shock, implied by semi-elasticities, $\{\hat{\beta}_h\}_{h=0}^4$, estimated from equation (1). The outcome variable is the cumulative change in the log of firms' debts, rather than of their capital stocks (Figure 2). The x-axis is the projection horizon, h. The dotted lines show the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.

E Findings for employment

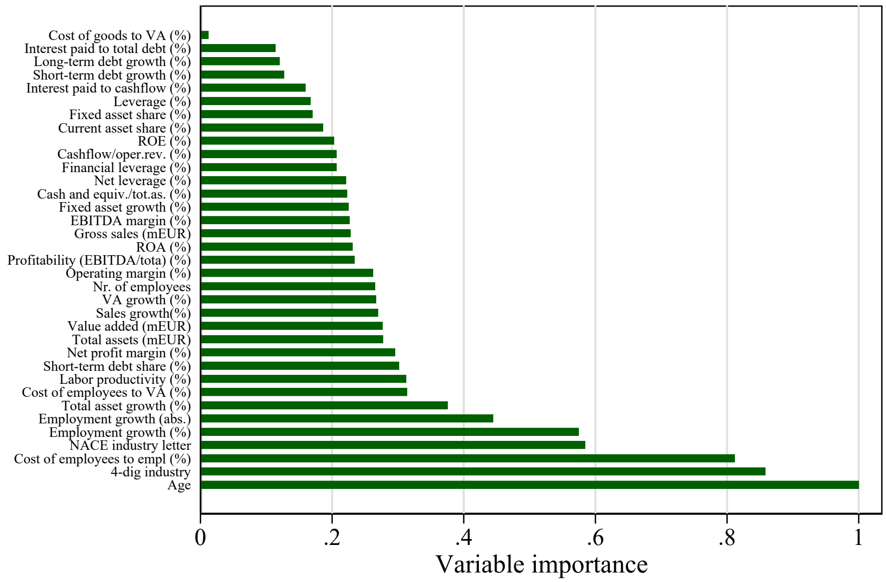
We rerun our main empirical exercises, but using employment instead of capital stock. First, we estimate a single semi-elasticity of firm employment with respect to the monetary policy shock at various horizons, $h = 0, 1, \ldots, 4$ years (equation (1)). We plot the implied impulse response function of a firm's employment to a 25 basis point contractionary monetary policy shock in Figure E.1. Next, we estimate firm-specific semi-elasticities (equation (2)) at a horizon of $h = 2$ years to match the timing of the peak of the magnitude of the common response. We use our Random Forest algorithm (Section 4.2) to detect the most important predictor of a firm's employment response to monetary policy shocks. The results—the variable importance of each predictor—are in Figure E.2. As for capital, age is the most important variable. Thus, following Section 4.3, we group observations by the age of the firm at the time of the shock, and estimate a single semi-elasticity of firm employment with respect to the monetary policy shock for each age group (equation (1)), using a horizon of $h = 2$ years. Figure E.3 plots the implied response of firm employment to a 25 basis point contractionary monetary policy shock across age groups.

Figure E.1. Average employment response.



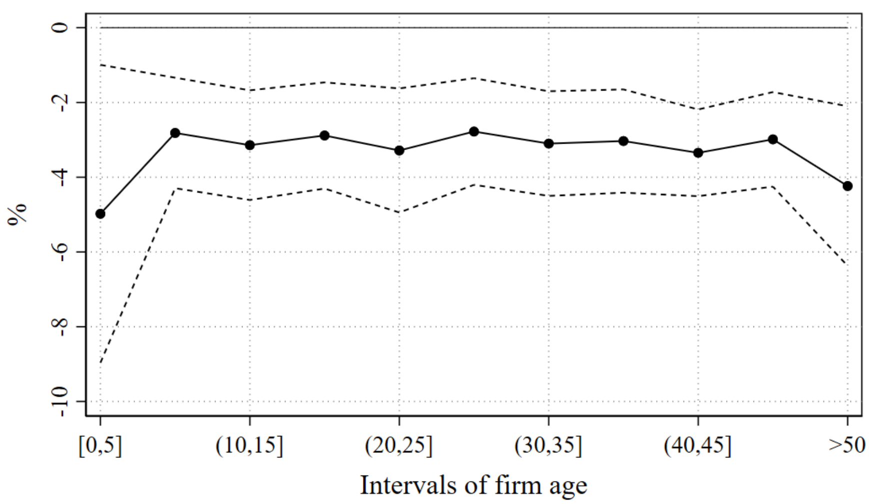
Note: The percentage response of firm employment to a 25 basis point contractionary monetary policy shock, implied by the common semi-elasticity estimated for all firms. The x-axis is the projection horizon, h. The dashed lines form the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.

Figure E.2. Variable importance of predictors of firm-specific employment semi-elasticities.



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

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



Note: The percentage response of firm employment to a 25 basis point contractionary monetary policy shock as a function of firm age, implied by semi-elasticities estimated separately for each age group using equation (1) with a horizon of $h = 2$ years after the shock. An observation is grouped based on the firm's age at the time of the monetary policy shock. The dashed lines form the 90% confidence intervals, based on two-way clustered standard errors by firm and year-month.