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

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Abstract

We study sources of heterogeneity in the response of firm investment to monetary policy. We estimate firm-level semi-elasticities of investment to plausibly exogenous changes in interest rates for a comprehensive firm-level dataset that covers ten euro area countries. Using a machine learning algorithm, we find that firm age best predicts differences in these micro elasticities across firms. Impulse response functions for different age groups reveal that investments of young firms are significantly more sensitive to monetary policy than investments of older firms. To rationalize this finding, we develop a model with convex and fixed capital adjustment costs. Older firms are less responsive to interest rate shocks because they are closer to their optimal scale, and thus less likely to pay the fixed cost. One key implication is that a shift in the firm distribution towards older firms implies a lower aggregate response to monetary policy.

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

JEL Classification: D24, E22, E44, E52

1 Introduction

The response of firms to interest rate changes 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.

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We use an agnostic data-driven 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-level semi-elasticity of investment 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 use a Random Forest algorithm (Breiman, 2001) to find which observable variables best explain variation in the estimated elasticities.

Firm age is the most important variable for explaining variation in investment elasticities across firms. In particular, it is a better predictor of a firm's investment elasticity over other variables by a wide margin, including firm size and financial variables such as firm leverage and a cashflow-based measure. The result holds whether or not we include the effects of firm entry and exit, and across time periods.

To quantify differences in the response along age, we use local projections (Jordà, 2005) to estimate separate impulse response functions for different age groups. 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 0.25 percentage points, the total fixed assets of firms between 0 and 5 years old are lower by seven percent, whereas the total fixed assets of firms around 40 years old are lower by only one percent. 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.

We demonstrate that a lifecycle firm model with capital adjustment costs can rationalize our findings. Firm production is decreasing returns to scale in capital, the only input. The interest rate is the user cost of capital and the rate firms use to discount future profits. Firms enter with a low initial level of capital and face no risk. They expand their capital stock 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. A change in the interest rate shifts a firm's optimal size. A young firm responds 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. As in the data, the age rather than the size of a firm is relevant. If a small firm is old, then it is likely unproductive, has a small optimal size, and is not willing to pay its fixed adjustment cost. If a large firm is young, then it is likely productive, has an even larger optimal size, and is still paying its fixed cost to grow further.

For now, we focus on a simple model of a single firm to illustrate the theory. Nonetheless, we can compare its qualitative predictions to the data. The important feature of the model is that as a firm ages, it grows closer to its optimal size, and so no longer wants to pay a fixed cost to adjust its capital stock. A direct prediction is thus that older firms are less likely to change their capital stock at all. In the data, older firms bunch a large share of their capital

[1] This identification strategy goes back to Kuttner (2001) and has found wide adaptation in the recent literature.

growth close to zero. A second prediction is that an older firm invests less as a share of its capital stock. In the data, the average percentage change in a firm's stock of fixed assets is decreasing with age. This holds both unconditionally, as well as controlling for firm size. In addition, the within-firm variation of fixed asset percentage changes falls with firm age.

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.

Related literature. This paper contributes to the literature on monetary policy transmission along different firm characteristics. Various dimensions have been shown to lead to heterogeneity in transmission to firms and the aggregate economy. These include 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 previous work, we take an agnostic data-driven approach to identify the most important characteristic for investment response heterogeneity across firms. The data we use include a broad set of firms, and so are particularly well-suited for this approach.[2]

We also contribute 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 the presence of 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 on the presence of 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 the role of capital adjustment costs for investment dynamics. Early papers by Caballero and Engel (1999) and Cooper and Haltiwanger (2006) find that fixed costs are important to match the lumpiness of investments in firm microdata. We provide indirect evidence for the importance of 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 potential proxy for whether it is constrained by fixed

[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 subsample of the firm distribution.

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 Sample construction

The firm-level data is from the Orbis database by Bureau van Dijk, which contains panel data of private and public firms. Our sample consists of 7.7 million non-financial firms for ten euro area countries over the time period 1999 to 2018.[3] The data is obtained from the recently launched Orbis Historical database, which contains the time series for each firm going back as far in time as possible. This overcomes earlier data limitations where Orbis data was only available for a fixed amount of years. The starting point of the data is chosen to coincide with the inception of the euro area. The data frequency is annual, and we observe the balance sheet and income statement as well as sector, age, number of employees, and other firm characteristics. For the cleaning of the data, we closely follow the detailed guidance by Kalemli-Özcan et al. (2019), as well as additional cleaning steps outlined by Durante et al. (2022). Last, we perform manual data checks and cleaning along 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 account closing date. Thus, the firm panel contains observations with year-month frequency. For consistency, we exclude observations where firms vary the month of reporting over time.[4] This ensures that the time between reports for any given firm is always twelve months. All financial variables are deflated with the monthly HICP index of the corresponding country where the firm is filing its report. To avoid outliers from distorting the results, we winsorize all variables, including growth rates and other transformations, at the 1% and 99% level. Appendix A.1 contains a list of all variables and transformations for the data used in the main part of the paper.

[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.

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

2.2 Sample description

The sample has very good coverage of the aggregate economies, and the distribution of firms by size is representative of the overall firm distribution. When summing up gross sales across all firms in the sample for each year, the coverage is larger than 60% for most sample countries, and for some as high as 80% (see Table A.2 in Appendix A.2 for the aggregated gross output shares across countries and time). In addition, the distribution of aggregated sales along firm size is close to the distribution in the respective countries. When calculating the share of sales by groups of firm size, measured in terms of employment, in Orbis and comparing them to the aggregate output share of the size group, the two line up well with some variation across countries (see Figure A.1 in Appendix A.2 for details).[5]

Table 1: Summary statistics 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 reported in million euros and have been deflated using the HICP index of the respective country with base year 2015. The number of employees is given as the number of persons employed. Firm age is reported in years and computed as the difference between the year of incorporation and the year of reporting.

Table 1 shows selected summary statistics, which reveal three sample properties. First, the number of observations is very large. Balance sheet information, here presented by total assets, are available for more than sixty million firm-year observations. The income statement is a bit less frequently reported, which shows a slightly lower but still very large number of observations of gross sales. Information on the number of employees is included for more than half of the firm-year observations in the sample. Importantly, the date of incorporation from which firm age is computed is widely available. Second, looking across the percentiles and up to the maximum observation, the distribution of firms is very wide. The average firm has around five million euros in total assets and is about thirteen years old, and firms in the upper part of the age and size distribution are significantly larger and older.[6] Third, the majority of firms are relatively small and young. At the median, the firm size in terms of total assets is only around 0.3 million euro, and even at the $90th$ percentile, the size is only about 3.3 million euro. Similarly, the median firm is ten years old and the vast majority of firms are not more than thirty years old. This reflects the fact that most firms in Orbis are privately held firms, which makes Orbis representative of the broad distribution of firms in the economy.

[5] For the comparison with aggregates the selection of sectors in the Orbis data has been adjusted to match those underlying the OECD data. Appendix A.2 provides further details on the comparison with the aggregate economies.

[6] The oldest firm in the sample is indeed older than 900 years. This is a German brewery, based in Bavaria, that is operating in the tradition of an old monastery.

3 Empirical framework

This section discusses the identification of exogenous monetary policy shocks in subsection 3.1 before laying out the baseline regression specification in subsection 3.2. The last subsection 3.3 presents the response for the average panel effect.

3.1 Identification of monetary policy shocks

The monetary policy shocks are identified using high-frequency surprises in short-term interest rates around Governing Council meetings of the European Central Bank (ECB) (see e.g., Kuttner (2001), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Altavilla et al. (2019) as well as Ramey (2016) for a discussion of this identification approach). The identifying assumption is that changes in interest rates computed over a narrow window around the policy decision are solely attributed to monetary policy and do not reflect other changes in aggregate conditions. Hence, they represent exogenous movements in interest rates that are triggered by the decision of the central bank. We obtain the intraday surprises for the meetings of the ECB Governing Council from the Euro Area Monetary Policy Event-Study Database (EA-MPD), provided by Altavilla et al. (2019).[7] In the analysis, we consider surprises in the 3-month OIS rate calculated over the entire event window, i.e., from before the press release to after the press conference.

Following Jarocinski and Karadi (2020), we use only surprises from events where interest rates and stock prices move in opposite directions. This way, it is possible to distinguish two different types of policy surprises that markets may infer from the Governing Council meeting and subsequent communication during the press conference. The monetary policy shock is one where an increase in the interest rate is accompanied by a fall in stock prices since the tighter policy stance is expected to lower output, which is reflected in a decline in the net present value of firms' cashflows. In contrast, a so-called "information shock" is one where market participants assume that the change in the interest rate is due to the fact that policymakers possess superior information over the economic outlook. In this vein, an interest rate increase could be a signal about benign expectations by policy makers, which in turn lead to an upward revision of stock prices.[8]

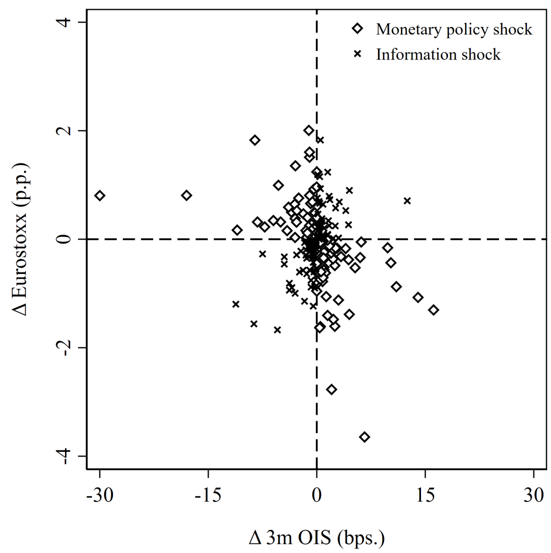
Figure 1 shows all surprises in the 3-month OIS rate plotted against the concurrent changes in the stock market index. As discussed, the analysis considers only events where the two asset prices have a negative correlation, namely those located in the second and the fourth quadrant marked with a diamond-shaped marker.

We examine the plausibility of the identified monetary policy shocks by estimating impulse responses to aggregate variables at the monthly frequency. Figure B.2 in Appendix B.2 shows the IRFs of the short-term euro area interest rate, GDP, total domestic investment and the GDP deflator in response to a contractionary monetary policy shock. The responses are in line with the patterns postulated by the literature. The shock leads to a significant increase in the short-term rate on impact, which initially rises further before it reverts. GDP and investments decline with a lag and reach a trough around two years after the shock while

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

[8] Examples of other papers that look at the distinction between these two types of central bank surprises are Andrade and Ferroni (2021) for the euro area and Nakamura and Steinsson (2018) for the U.S.

Figure 1. Stock price and policy rate surprises.



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

prices decline beyond that.

To match the surprises with the firm-level data, we aggregate them to the annual frequency. Since the month of reporting varies across firms, we compute the twelve-month moving sum of the surprises. The firm reporting in a given month is then linked to the sum of all monetary policy surprises in the twelve months up until the filing date. This ensures the largest possible time variation in the monetary policy shock series. Figure B.1 in Appendix B.1 shows the time series of the shock.

In order to validate this aggregation of the shocks, we follow Holm et al. (2021) and compare the response of macro variables that are available at the monthly and the annual frequency. Figure B.3 in Appendix B.3 shows the trough of the impulse responses of GDP and investment for monthly and annual data. The exercise confirms the magnitude of monetary policy transmission to the macroeconomy for aggregation across the two frequencies.

3.2 Baseline specification

Impulse response functions (IRFs) to the identified monetary policy shocks are estimated on the firm panel using the local projections method by Jordà (2005). The baseline specification is detailed in equation (1) and a separate regression is estimated for each projection horizon $h \in \{0, ..., 4\}$.

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

The outcome variable $\Delta_h Y_{i,t+h}$ is the cumulative change in the stock of tangible capital $k_{i,t}$ of firm i. It is measured as the log-difference between the period before the shock $t-1$ and $t+h$, that is $\Delta_h Y_{i,t+h} \equiv \log(\mathrm{k}_{i,t+h}) - \log(\mathrm{k}_{i,t-1})$. $\alpha_{i,h}$ is a firm fixed effect. The term $shock_t^{MP}$ is the identified monetary policy shock as described in subsection 3.1, and the sequence of coefficients $\{\hat{\beta}_h\}_0^4$ yields the IRF along the projection horizons denoted by h. The standard error of $\hat{\beta}_h$ is used to construct the corresponding confidence interval of the IRF. The vector X_{t-1} contains lagged macroeconomic controls. They are the year-on-year growth in industrial production and the price index at the country level. Last, standard errors are two-way clustered at firm and time, where time is the year-month, in line with the variation of the monetary policy shock series. The treatment of the standard errors thus takes into account potential serial correlation within a firm over time as well as correlation across firms in a given month due to other common influences.

The baseline estimation can easily be extended to allow for heterogeneity in transmission across firm groups as per equation (2):

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \sum_{g=1}^{G} \alpha_{h,g} \times Dg_{i,t} + \sum_{g=1}^{G} \beta_{h,g} shock_t^{MP} \times Dg_{i,t} + \sum_{g=1}^{G} \Gamma'_{h,g} X_{t-1} \times Dg_{i,t} + \epsilon_{i,t+h} \quad (2)$$

Here, the main terms from the baseline regression (1) are interacted with a group dummy $Dg_{i,t}$, which is equal to one if firm i is part of group g in year t and zero otherwise.[9] This leads to potential differences in the respective regression coefficients across groups. In particular, the sequence of coefficients $\{\hat{\beta}_{h,g}\}_0^4$ represents the IRF for each group $g \in \{1, ..., G\}$. The common estimation across groups further allows for inspecting the statistical difference in transmission between groups. Specifically, if group $g = 1$ is the designated base group for which the IRF is estimated in (2) from the term $shock_t^{MP}$ alone, the estimates of $\{\hat{\beta}_{h,g\neq 1}\}_0^4$ gauge the impact of monetary policy for all other groups relative to the base group.

3.3 The average effect

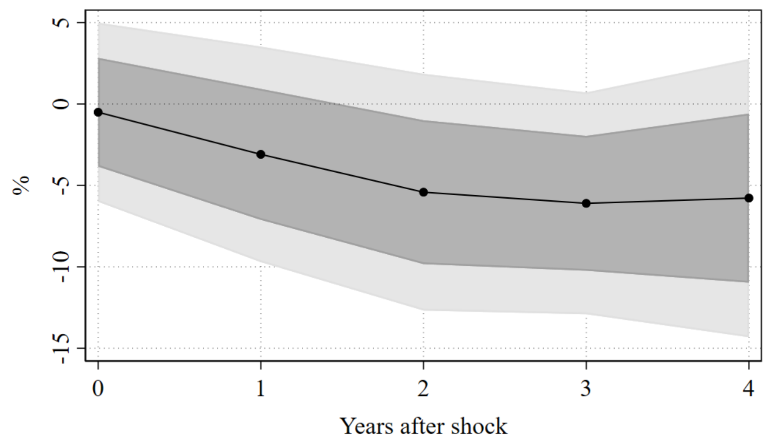
Figure 2 presents the firm-level investment response to a $25bps$ monetary policy tightening shock (interest rate increase) across the full sample, i.e., the average response. Investments fall in response to the rise in interest rates and reach a trough of -6.1% after three years with an estimate that is borderline significant. The decline gradually builds up, which is in line with the notion that the effect of monetary policy on the real economy transmits with a time lag. The magnitude lies in the range of average investment responses estimated by Crouzet (2021) and Cloyne et al. (2022), who obtain a trough effect of -4.8% and -6.5%, respectively. Based on the observation that, on average, investments decline for firms in the sample, we next investigate heterogeneity in responses across firms.

4 Heterogeneity in transmission

We now estimate firm-level investment elasticities (subsection 4.1). We then use a machine learning algorithm to detect relevant firm characteristics that predict differences across firms (subsection 4.2). Subsequently, we describe the relationship between the most important firm

[9] If the dummy is set to one for all firms and year-months, equation (2) is the same as the baseline equation (1) yielding the average effect across the entire sample.

Figure 2. Average investment response.



Note: The figure shows the response of investment to a 25*bps* monetary policy tightening shock as per equation (1). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon h shown along the x-axis. The light (dark) gray area is the 90% (68%) confidence interval. The confidence intervals are based on two-way clustered standard errors by firm and year-month.

characteristic and the transmission of monetary policy (subsections 4.3 and 4.4), and examine the robustness of the findings (subsection 4.5).[10]

4.1 Firm-level elasticities

To obtain firm-level responses to monetary policy, we estimate the following equation for each firm separately

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \beta_{i,h} shock_t^{MP} + v_{i,t+h} \tag{3}$$

where, as before, the outcome variable is the cumulative log-change in fixed assets from the period before the monetary policy shock $t-1$ and $t+h$. $\alpha_{i,h}$ presents a firm-specific constant and $shock_t^{MP}$ is the identified monetary policy shock series. The estimate of interest is $\hat{\beta}_{i,h}$, which measures the semi-elasticities of firm i's investment to monetary policy. In line with the timing of the trough in the average response from Figure 2, we estimate the elasticity three years after the shock, i.e., for $h = 3$.

Figure 3 shows the distribution of firm-level semi-elasticities to a 25*bps* increase of the monetary policy shock.[11] The average is -4.8% and the median -4.1%, which are close to the magnitude of the panel average. A large fraction of estimates are actually positive, unlike the average transmission response, and counter to the typical prediction that firms reduce their capital stock in the face of a higher cost of capital. In addition, many of the estimates are large. This in part reflects the uncertainty around the estimates, which are obtained from

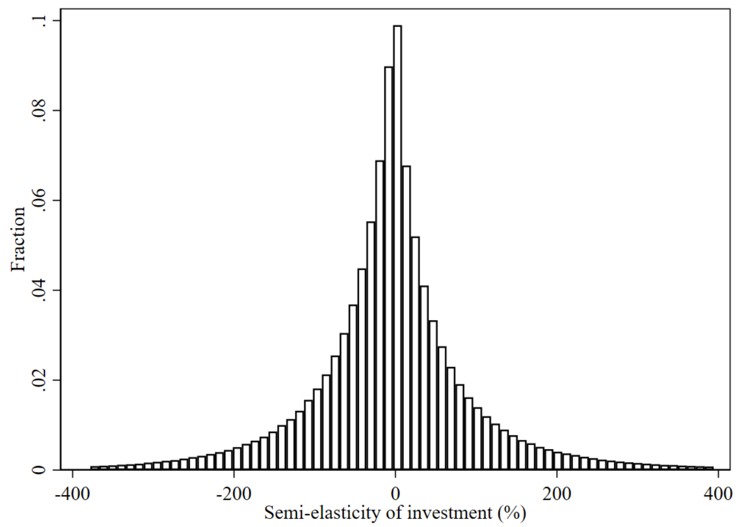
[10] The main outcome variable of the paper is investment. In Appendix F, we present results for the same analysis using employment.

[11] The elasticities are obtained for around 2 million firms in the sample. Since the outcome variable computes the difference in the capital stock over several years, the elasticities can only be estimated for firms with observations over at least five years. In order to keep the maximum possible degrees of freedom, no controls are added to the estimation equation (3).

a relatively small set of observations for each firm. When restricting the sample to firms with a higher number of observations, the dispersion in the estimated elasticities becomes more narrow. Hence, the exact magnitude of the firm-level estimates should be interpreted with caution. In the following analysis, we also consider subsamples of elasticities, which are based on *(i)* only firms for which the elasticity is estimated based on a larger amount of observations as well as *(ii)* estimates that are statistically significant at the 10% level. Histograms of the subsamples are plotted against the full set of elasticities are available in Appendix C.[12]

The heterogeneity in elasticities reveals that firms' responses to monetary policy can vary widely. With this large set of micro-level estimates, we now investigate which firm characteristics best predict variation in firm-level responses.

Figure 3. Histogram of semi-elasticities of investment at $h = 3$.



Note: The figure shows the distribution of firm-level semi-elasticities to a 25bps contractionary monetary policy shock. The distribution is cut at the top and bottom 1% and the number of bins is set to 70. Values outside of $[-100\%, +100\%]$ can be obtained since the change in the capital stock is computed using logs.

4.2 Detecting relevant firm characteristics

To establish which observable characteristics can predict differences in the estimated elasticities $\hat{\beta}_{i,h}$ across firms, we use an agnostic data-driven approach: a Random Forest algorithm (Breiman, 2001). The algorithm identifies sample splits along observable characteristics that maximize variation in the outcome variable. This procedure has two key advantages. First, it allows for non-linearities between the outcome variable and characteristics as well as among explanatory characteristics, which appear important when studying the transmission mechanism of monetary policy. Second, it does not suffer from the otherwise occurring statistical

[12] The subsamples reveal that the distribution is less dispersed for elasticities that are estimated from at least ten observations per firm (see Figures C.1 and C.2). When considering only statistically significant estimates, shown in Figure C.3, the distribution becomes more dispersed, and the share of negative estimates is larger. Yet, the standard errors are not based on a large number of observations, so this subsample selection should be treated with caution.

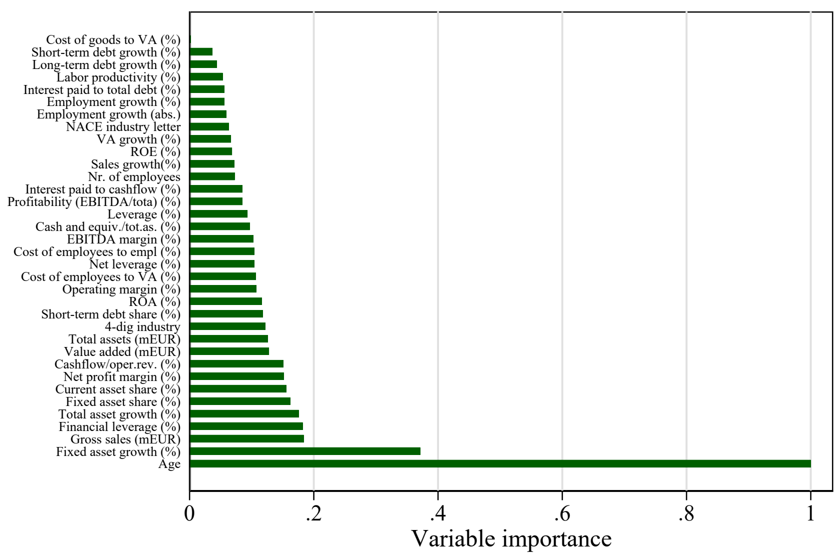
issues from multiple hypotheses testing. A stylized example of the algorithm is illustrated and discussed in Appendix D.

The outcome variable in the algorithm is the firm-level semi-elasticity of investment to monetary policy, which is estimated as outlined in the previous subsection. We define a set of thirty-five explanatory variables $\bar{x}_i \in \bar{\mathbf{X}}_i$, which consist of 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 list of the characteristics is in Appendix D. To map firm-level elasticities to these variables, we compute the time-average of each variable $x_{i,t}$ for firm-i over the sample.

Figure 4 shows the variable importance of each potential characteristic for explaining the investment elasticity. The Random Forest algorithm generates the variable importance measure, which indicates how much the predictability of the elasticity would decline if a variable were excluded from the set of candidate variables. Since this is always relative to the set of variables that are considered, we can only compute the relative importance of each variable; the most important variable is normalized to one.

The plot reveals that firm age is the most important variable by a large margin. Hence, our agnostic approach confirms previous work by Cloyne et al. (2022) and Durante et al. (2022) that highlight age as a relevant firm characteristic for transmission heterogeneity. The annual change in total fixed assets is ranked second, and the remaining variables are much less important.

Figure 4. Variable importance of the semi-elasticity of investment.



Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of investment to monetary policy estimated from equation (3) at $h = 3$. The set of potential explanatory variables is listed along the left side of the chart. "VA" stands for value-added. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

Evaluating the R^2 measure from the Random Forest also reveals firm age as a highly important variable for explaining variation across firm-level elasticities. Specifically, we compare the R^2 measure from separate runs of the algorithm, dropping one covariate at a time. When excluding firm age from the set of potential regressors, the measure of R^2 drops significantly, whereas it changes only modestly in the runs where we exclude any of the other covariates.

Alternative Random Forest specifications. We conduct a few checks of this baseline setup of the Random Forest. All confirm firm age as an important variable. The variable importance of these alternative evaluations is in Appendix D.3. First, we vary the set of covariates and exclude variables that have a high correlation. The aim of this is to ensure that a low measure of variable importance for one variable does not simply reflect the presence of other correlated variables. The results are in Figure D.2. A second set of specifications uses varying subsamples of the underlying $\hat{\beta}_{i,h}$-estimates.[13] First, we check whether the algorithm potentially picks up variation in the elasticities by age due to noise in the estimates of young firms which are estimated based on fewer observations. When looking at the distribution of elasticities across firm age, it is indeed the case that the distribution is wider for younger firms. To obtain a comparable degree of noise, we run the algorithm on a subset of firm-level elasticities that have been estimated from ten observations.[14] On this subset, the unconditional change in fixed assets becomes the most important variable, followed by firm age in second place (see Figure C.1 for the distribution of elasticities and D.3 for the variable importance). In addition, we consider only elasticities that are estimated based on at least ten observations shown in Figure C.2. The resulting variable importance ranking is the same as for ten observations, however age obtains a relatively higher degree of importance (see Figure D.4). Last, we run the Random Forest only on elasticities that are estimated with statistical significance at the 10% level. Here, age is again ranked as the most important variable by a large margin (see Figure C.3 for the distribution of elasticities and D.5 for the variable importance).

Informed by this exercise, we next explore the direction and the magnitude of the relationship between firm age and the transmission of monetary policy to investment.

4.3 Transmission across firm age

To trace out the relationship between firm age and monetary policy transmission to investment, we group firms in age intervals, and estimate the group-specific IRF as specified in equation (2). This non-parametric estimation yields a separate response for each age interval, and so traces out differences in transmission along age. For the grouping, we define intervals of five years of age up until age fifty, and one group for all firm-year observations where a firm is older than fifty years. A firm is assigned to a group based on the age at the time of the monetary policy shock. A firm can thus be assigned to different groups over time.

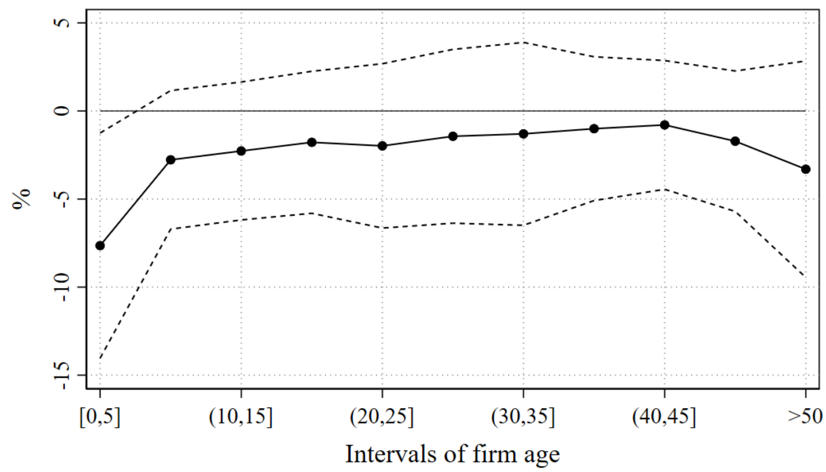
Figure 5 shows the response to a 25*bps* increase in the monetary policy shock along age for the projection horizon $h = 3$ with the 90% confidence interval. The response is most negative for young firms, and increases toward 0 with age. The gradient is particularly steep at the beginning of the firm age distribution. Firms until age five see a reduction in the stock of fixed assets by 7.6%, compared to only 2.7% for firms in the second youngest interval between ages

[13] Although these subsamples reduce the number of elasticities, there are still many observations left. Considering the subset of firms with at least ten observations or with exactly ten observations, the number of firms is reduced to about 1 million and 263,000, respectively. For the subsample of elasticities that are statistically significant, the number of observations falls to about 257,000.

[14] Ten observations corresponds to the average amount of observations of firms for which an elasticity at $h = 3$ can be estimated.

five and ten. Subsequently, the magnitude of the response reduces gradually, and is smallest for firms between age forty and forty-five with a fall of 0.8%.[15] Taking into account confidence intervals, the response is statistically significant only for firms in the lowest age group.

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



Note: The figure shows the response of investment to a 25bps monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The dashed line is the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

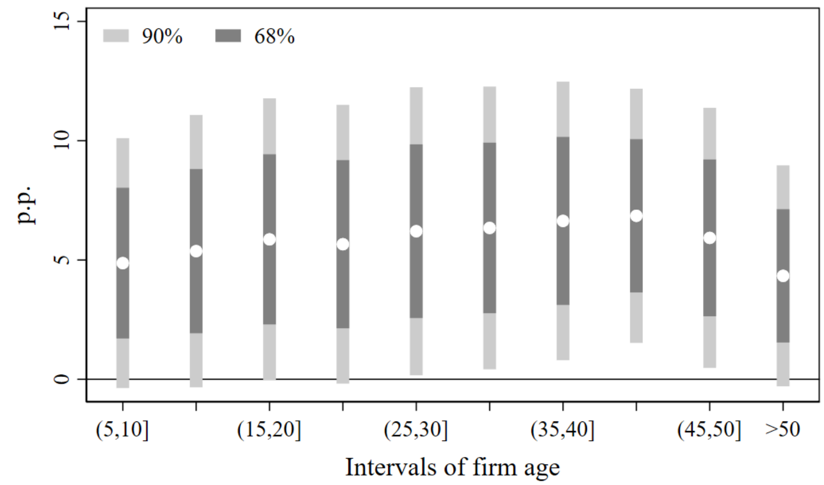
Figure 6 shows the difference in responses to a 25bps increase in the monetary policy shock at $h = 3$ of all age groups relative to the youngest group. The white dots are the differences in the point estimate and the gray bars the confidence bands, which convey whether the differences are statistically significant at the 90%- and 68%-level. The positive differences across all point estimates reflects that the responses for older age groups are less negative than for the youngest group. The difference increases from 4.9 to 6.8 percentage points and falls again for the last two age groups. The differences are all statistically significant at the 68% confidence level, and between twenty-five and fifty years of age are statistically significant at the 90% confidence level.

4.4 Contribution to the aggregate response

The strong response of young firms raises the question of how much this group contributes to the aggregate change in capital in response to monetary policy. To evaluate this, we decompose the change in the aggregate capital stock K into the capital change of each age

[15] Figure E.1 in Appendix E.1 shows an extended version of the chart with intervals ranging until age one hundred fifty. For higher ages the estimates become slightly erratic and the confidence intervals widen, which also reflects a smaller number of observations for those intervals. Hence the main results collect all observations of age fifty and higher in one group.

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



Note: The figure shows the differences in investment responses along age groups relative to the youngest group to a 25*bps* monetary policy tightening shock. The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The light gray (dark gray) bars show the 90% (68%) confidence interval. The confidence intervals are based on two-way clustered standard errors by firm and year-month.

group j as follows:

$$\Delta K_t = \sum_j \omega_{j,t}^k \dot{k}_{j,t} \tag{4}$$

where $\omega_{j,t}^k = \frac{k_{j,t}}{K_t}$ denotes the share of capital of group j in the aggregate capital stock and $\dot{k}_{j,t} = \frac{\partial \Delta k_{j,t}}{\partial \text{shock}_t^{MP}}$ is the response in the capital stock of group j to the monetary policy shock. At a time period t, we consider the response horizon after three years, $h = 3$, to capture the cumulative trough effect. The weights of each group $\omega_{j,t}^k$ are computed from the microdata, where we take the average of the share of capital for each age group over the previous three years in the sample.[16]

The weighted sum of firm-group responses implies a decline of 2.3% in the aggregate capital stock in response to a 25*bps* increase in interest rates. The decomposition of the aggregated sum shows that the youngest firms of age zero to five account for as much as 35% of the aggregate response in the capital stock to monetary policy. This is despite such firms accounting for only 11% of the *level* of the aggregate capital stock. By contrast, firms older than twenty-five hold 43% of the capital stock, and their capital adjustments in response to monetary policy are responsible for only 22% of the aggregate response. This demonstrates that the large investment sensitivity of young firms has sizable effects on the overall economy.

[16] For this exercise, we consider a total of five age groups based on the gradient in the responses from Figure 5. The first three intervals are the same, and we sort firms older than fifteen into two groups, one from ages sixteen to twenty-five and one for firms older than twenty-five.

4.5 Robustness

We now present a series of robustness exercises for the finding of heterogeneous transmission along firm age. All estimations considered confirm the baseline findings. Although some robustness specifications result in wider confidence intervals, the gradient in the point estimate along age remains. The outputs are in Appendix E.2.

Firm subsamples and controls. One potential reason why younger firms show a larger response of investment could be that they are more likely to exit, which would inflate the effect of monetary policy on the stock of fixed assets. To test whether the observed pattern is driven by differences in firm exit along age, we limit the sample to firms that are active through the entire horizon considered in the IRF estimations, i.e., firms with observations four years after the monetary policy shock is dated. The heterogeneous effects persist in the subsample of surviving firms (see Figure E.2). Similarly, entrants are possibly more susceptible to changes in the aggregate environment, which could lead to large adjustments in investment for the youngest age interval. To check whether the large investment response is driven by entrants, we exclude firms that are younger than three years old from the estimation. Again, the pattern along age remains, as can be seen in Figure E.3. Another concern is that firm age represents firm size and in itself does not lead to differences in transmission once firm size is taken into account. We test for this by controlling for differences in responses along firm size. Specifically, we add an interaction of the monetary policy shock and lagged firm size, measured as the log of total assets, to the regression and check whether the age gradient persists. Again, the finding that younger firms respond more strongly to monetary policy than older firms continues to hold (see Figure E.4).

Changes in the monetary policy environment. The sample period is characterized by major changes in monetary policy conduct. To test for potential differences in monetary policy transmission over time, we proceed in two ways: we estimate the regressions *(i)* on different sub-samples and *(ii)* with an aggregate control of a short-term shadow rate estimate, which captures interest rate changes in the presence of a lower bound. For both approaches, the results continue to hold (see Figures E.5 to E.7).

For *(i)*, we re-run the estimations with two sample splits using only observations through 2011 and 2013, respectively. The former is the point in time when 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. 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. Hence, the timing for the second sample split. The patterns from the baseline remain in these subsamples.

For *(ii)*, we use the full sample and add a summary measure of various shadow rate estimates as an aggregate control variable. These shadow rates capture the possible realization of what the policy rate would be if there were no lower bound. Since shadow rate estimates are sensitive to the method by which they have been derived, we follow Hartmann and Smets (2018) and extract a principal component from a total of five shadow rate estimates, namely those by Lemke and Vladu (2017), Kortela (2016), Krippner (2015), Wu and Xia (2020), using two versions of the rate by Lemke and Vladu (2017). We add the shadow rate to the baseline regression as a lagged control variable. Our findings continue to hold.

5 Theoretical framework

We now propose a theoretical framework to rationalize the heterogeneous responses along age (subsection 5.1). We then show that key model predictions hold in the data (subsection 5.3). Finally, we demonstrate that an alternative mechanism based on financial frictions does not fit the data (subsection 5.4).

5.1 Dynamic model of investment

The model abstracts from households and focuses only on the firm side. Furthermore, the analysis is in partial equilibrium, i.e., we focus on only a single firm, holding fixed aggregates and prices other than the interest rate.[17] Capital is the only factor of production, which the firm rents at an exogenous rental rate r. In each period, the firm chooses capital subject to 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 nonconvex fixed cost that is independent of the size of the change. The firm chooses capital to maximize the expected present discounted value of profits. They use the interest rate r to discount future payoffs, which is the same as the rental rate.[18] The firm faces no risk.

The firm's value function $V(k)$ solves the following Bellman equation:

$$V(k) = \max_{k'} z(k')^{\alpha} - rk' - \Psi(k', k) + \frac{1}{1+r} V(k'), \tag{5}$$

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

$$\Psi(k', k) = \mathbb{1}(k' \neq k)\chi_0 + \frac{\chi_1}{2}\left(\frac{k' - k}{k}\right)^2 k, \tag{6}$$

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

To understand the firm's problem, it is useful to split it into two steps. First, the firm chooses whether to adjust its capital stock at all, 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,

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

[17] Koby and Wolf (2020) show that investment lumpiness induced by capital adjustment costs as proposed in this framework play a role even in general equilibrium dynamics.

[18] We can allow for capital depreciation, in which case the rental rate is the interest rate plus depreciation.

subject to $k' \neq k$, and

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

where capital is fixed at its previous value.

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 evolution of the firm's capital is guided by two key thresholds. First, there is a k^* that maximizes revenue minus rental costs:

$$k^* = (r/z\alpha)^{\frac{1}{\alpha-1}}.$$

Absent adjustment costs ($\chi_0 = \chi_1 = 0$), the firm will immediately set its capital stock to k^* and remain there forever. Second, with the fixed cost ($\chi_0 > 0$), there is a $\bar{k} < k^*$ such that if the firm's capital is $k \in (\bar{k}, k^*)$, then the benefit of adjusting is lower than the fixed cost. In that case, the firm's capital remains constant forever.

Thus, a firm's capital slowly increases (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, a 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 choice of capital (in logs) against firm age for different types of adjustment costs. The solid black line at the top of the charts is the optimal scale $\ln(k^*)$. In the absence of a capital adjustment costs (subplot a), the firm immediately moves to its optimal size, and remains there forever. With only a fixed adjustment cost (subplot b), the firm again jumps immediately to its optimal size. The initial size is sufficiently small so that the benefit of adjusting 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 still grows toward the same optimal size, but only slowly because it is optimal to smooth adjustments over time. Moreover, the firm makes larger percentage adjustments when young, and 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 its optimal size 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, with only convex adjustment costs, the firm slowly adjusts forever, whereas with the fixed cost, in finite time, the firm stops adjusting.

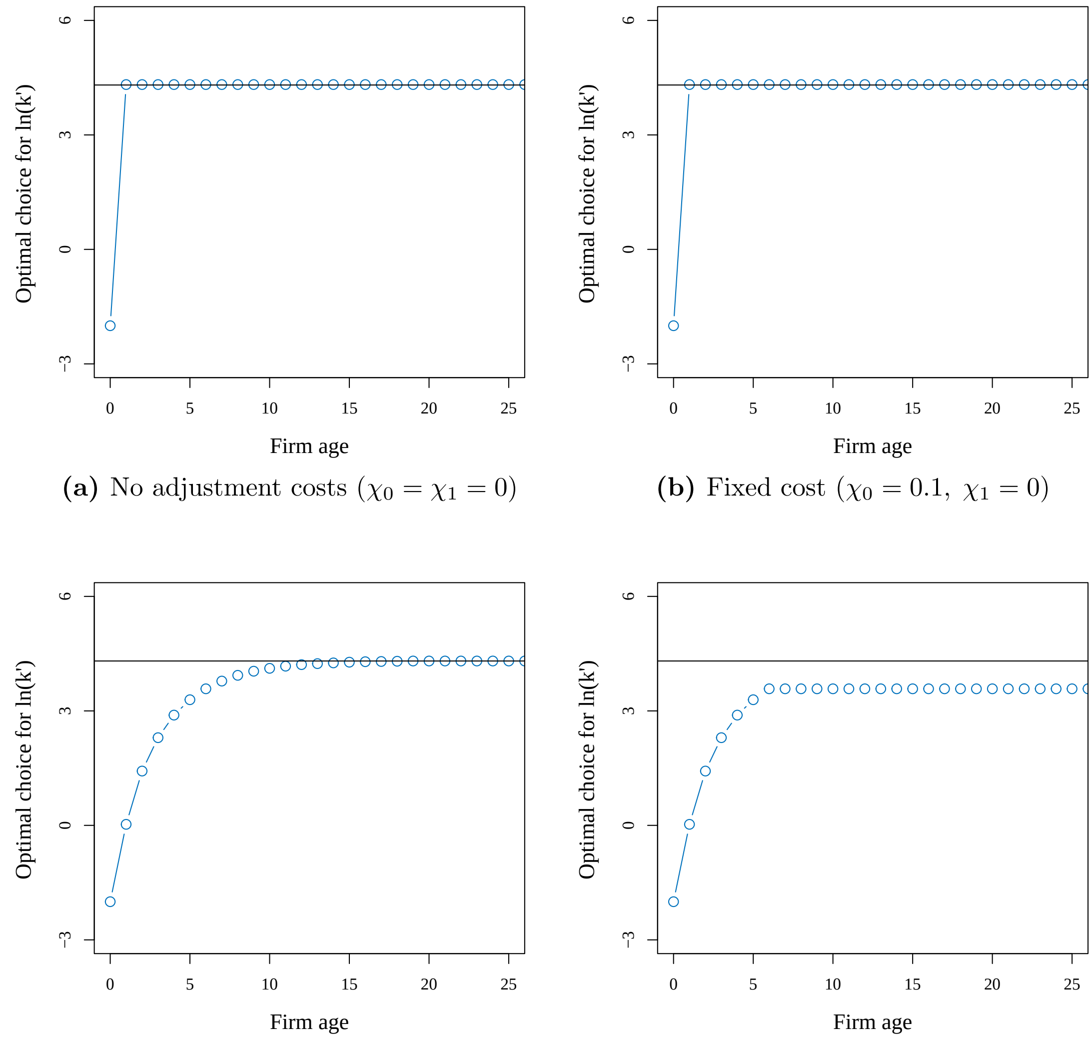
5.2 The effects of an interest rate shock

We now study how the firm responds to an unanticipated interest rate shock. In particular, we show how the response depends on the firm's age. The shock moves the interest rate from the long-run level r to $r + \varepsilon_0$. Subsequently, the shock dies out with persistence ρ. Formally, the evolution of the interest rate is

$$r_t = r + \varepsilon_t \qquad \text{with} \quad \varepsilon_t = \rho\varepsilon_{t-1}, \tag{7}$$

where t is periods since the shock. Figure 8 shows the deviation of the interest rate from its initial level over time.

Figure 7. Capital choice along firm age (steady state).



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

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

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

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

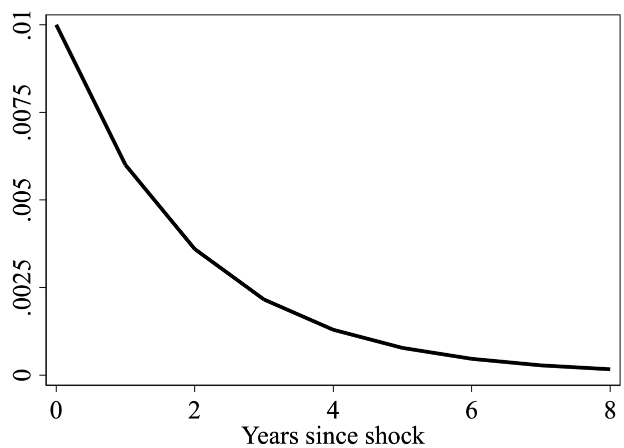
Note: The x-axis shows firm age measured as years since entry and the y-axis is the (log of) the optimal choice of capital k'. The blue dots show the policy function. The solid black line indicates the optimal capital stock k^* absent any adjustment costs.

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

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

where ε is the current interest rate shock, and $\rho\varepsilon$ is therefore the shock in the following period. The interest rate affects the capital rental rate as well as the rate at which the firm discounts the future. Intuitively, a rise in each rate lowers the firm's capital choice given its previous period capital. First, an increase in the rental rate raises the period cost of capital. Second, part of the value of increasing the capital stock is having more capital in the future, which raises future profits (since the firm is below its optimal level k^*).

Figure 8. Path of interest rate shock.



Note: The figure shows the evolution of the interest rate shock, which materializes at period $t = 0$ and has a persistence of $\rho = 0.6$.

Figure 9 displays the impulse response (IRF) of capital to the interest rate shock for a young firm and an old firm.[19] The blue line is the IRF for a firm of age five and the black dashed line for a firm of age fifteen.[20]

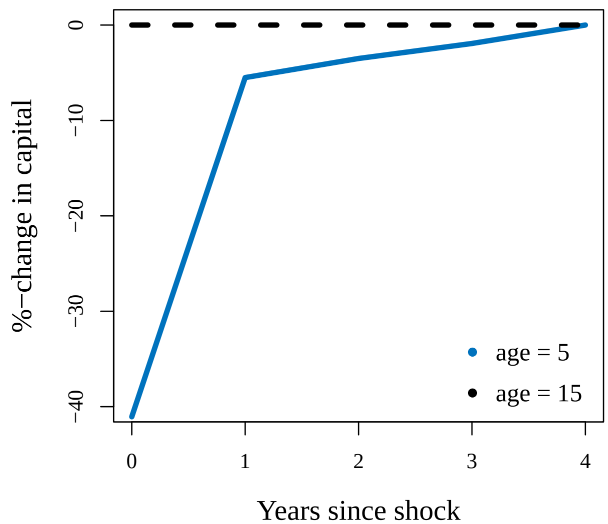
The two IRFs show that the model qualitatively delivers our main result: younger firms are more responsive to monetary policy shocks. The capital stock of the young firm is immediately lower than it would have been without the shock. As the shock fades, the young firm's capital stock returns to what it would have been. On the other hand, the capital stock of the old firm is unaffected by the shock. The old firm would not have paid its fixed adjustment cost absent the shock, and does not with the shock either. This can be because the shock is sufficiently small that even if it were permanent, the old firm would not want to pay its fixed adjustment cost to respond. Moreover, since the shock fades over time, the firm is reluctant to pay to decrease its capital stock just to pay again to increase it later.

Age vs. size. In the current model, there is an exact relationship between firm age and size. We can easily extend the model to incorporate permanent productivity heterogeneity across firms. In this case, conditional on size, a young firm must be more productive that an older firm because it grew to that size more quickly. As such, a young firm is further from its optimal size, and so more likely to pay its fixed adjustment cost. On the other hand, conditional on age, a small firm is less productive than a larger firm because it grew more slowly. As such, it is closer to its optimal, and so less likely to pay its fixed adjustment cost. Therefore, as we find empirically, young firms will be more responsive to monetary policy shocks than older firms, but the same is not necessarily true for small firms vs. larger ones.

[19] The IRF is obtained by computing the difference in the choice for the (log) capital stock after the interest rate shock relative to the choice in the absence of the shock.

[20] Ages are at the time of the shock.

Figure 9. Impulse responses across firm age.



Note: The x-axis shows years since the initial period of the interest rate shock and the y-axis is the change in capital stock in percent. The black dashed line is the response of firms of age fifteen and the blue solid line is the response for firms of age five at the time of shock. The model features fixed and quadratic capital adjustment costs ($\chi_0 = 0.1,\ \chi_1 = 0.05$).

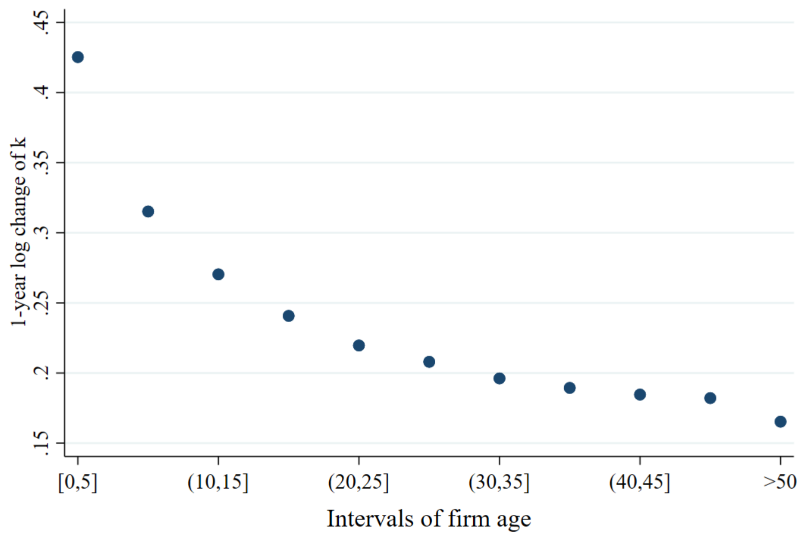
5.3 Testable model predictions

We now use our data to test key predictions of the model. First, the model implies that younger firms grow their capital stock faster than older firms. Second, that older firms tend to keep their capital stocks fixed. We find evidence for both predictions.

Figure 10 shows the median of positive year-on-year growth rates in total fixed assets by firm age. Younger firms are more likely to experience high growth rates. For firms up to the age of five years, the median positive change in fixed assets over one year is close to 45%, and it is only around 20% for firms older than thirty. The pattern holds when *(i)* controlling for firm size as shown in Figure G.1 in Appendix G and *(ii)* when considering within-firm variation by regressing the growth rate of fixed assets on age and a firm fixed effect.

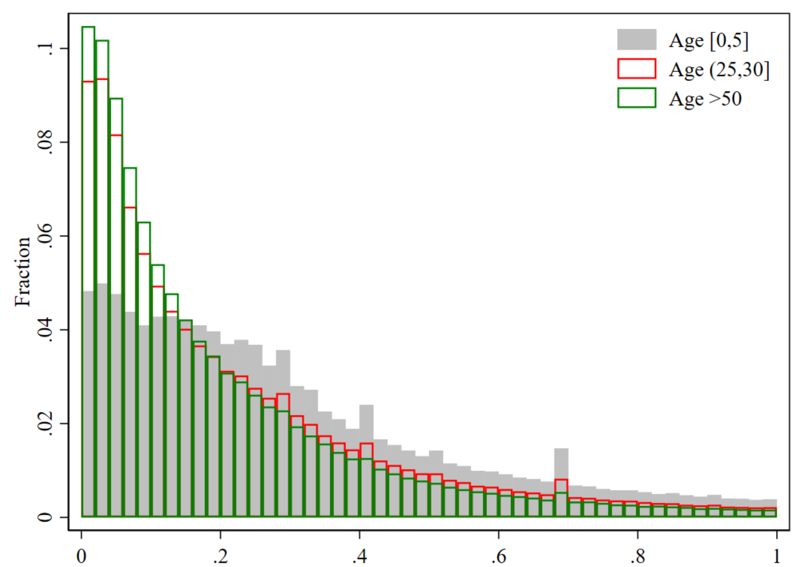
Figure 11 shows the unconditional distribution of absolute changes in fixed assets by firm age. Older firms tend to have a sizeable fraction of investments close to zero, which is in line with the key model prediction that such firms are less likely to pay the fixed adjustment costs necessary to make any adjustment. The youngest firms (gray bars) have very little inaction, i.e., there are few observations where the change is close to zero. By contrast, as firms get older (red and green bars), significantly more capital adjustments are bunched close to zero. The cumulative distribution function of absolute fixed asset growth in Figure G.2 in Appendix G shows that for the oldest firms, the median adjustment is around 14%, whereas the median adjustment is around 27% for the youngest firms.

Figure 10. Fixed asset growth by firm age.



Note: The figure shows a binscatter plot of the unconditional one-year growth rate in fixed assets across firm age. The dots are the median positive growth rate by age group in percent of the stock of fixed assets in the previous year.

Figure 11. Distribution of fixed asset growth across age groups.



Note: The figure shows the distribution of absolute unconditional changes in total fixed assets over one year. The distribution is plotted for three groups of firm age: firms that are at most five years old (gray), between twenty-five and thirty years of age (red) and older than fifty years (green). The number of bins is set to fifty and values are cut at one (100%).

5.4 Alternative mechanism: financial frictions

The proposed mechanism for rationalizing heterogeneous responses to monetary policy across firm age relies solely on investment frictions. The most prominent competing theory for explaining heterogeneity in monetary policy transmission to firms instead rests on the presence of financial frictions, in particular frictions related to the availability of debt (see, e.g., Gertler and Gilchrist (1994), Jeenas (2019), Ottonello and Winberry (2020), Cloyne et al. (2022), Durante et al. (2022)). Monetary policy affects the availability of debt by changing borrowing costs and the valuation of collateral that might be pledged to obtain external credit. Based on the notion that investments are often financed through external borrowing, changes to borrowing conditions can ultimately affect investment decisions of firms. This section discusses whether financial frictions can explain our finding that younger firms are more responsive to monetary policy.

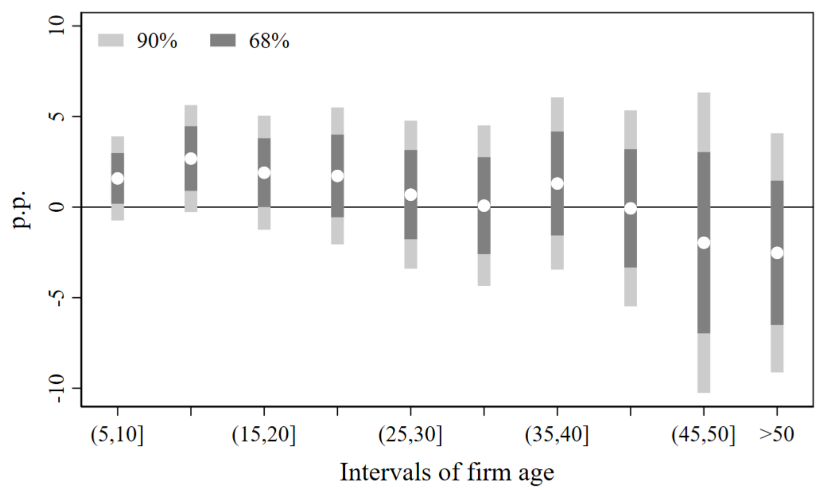
Potential mechanisms based on financial frictions. One relationship between financial frictions and firm age is that younger firms are likely more financially constrained because they have not been able to establish strong relationships with creditors, are still building a customer base, and experience larger profit volatility.[21] In this case, however, young firms should also be more limited in their ability to adjust investments to the cost of capital, which would lead to the prediction that they are less responsive to monetary policy. This relationship between financial frictions and investment responses is in line with the mechanism that Ottonello and Winberry (2020) highlight, where more financially constrained firms face a steeper marginal cost curve for financing investments. This relationship between financial frictions and firm investment decisions would thus not align with the empirical findings.

Another relationship between financial frictions and firm age is that younger firms' borrowing constraints may be more sensitive to monetary policy. The classic borrowing constraint is one where the amount of debt depends on the value of collateral that the firm pledges to creditors. Since changes in interest rates lead to changes in asset values, monetary policy leads to the easing or tightening of such constraints. For there to be a differential effect across firm age, it would need to be the case that firms of different ages borrow against different types of collateral, which in turn have different valuation sensitivities to interest rates. Bahaj et al. (2022) provides evidence for this: they show that younger firms more often use the private home of the firm owner as collateral, and housing values are particularly sensitive to monetary policy. However, recent papers have documented that most borrowing constraints are instead linked to firm revenues (Lian and Ma, 2020, Drechsel, 2023). Through indirect effects of monetary policy on firm revenues, changes in interest rates would also affect these types of borrowing constraints. Yet, this would require another argument for why revenues change to a varying degree along firm age for inducing differences in borrowing sensitivities. Overall, this discussion highlights that it is not straightforward to rationalize the empirical findings with financial frictions, and that several additional assumptions need to be made for establishing such a mechanism. In addition, though financial frictions likely play a role in the transmission process of monetary policy, they can be hard to identify in empirical settings, which makes it difficult to validate related mechanisms.

[21] The papers of Cloyne et al. (2022) and Durante et al. (2022) explicitly consider firm age as a proxy for financial constraints.

Empirical tests for financial frictions. We conduct several tests for whether the larger responsiveness of younger firms is due to financial frictions. We do not find evidence that this is the case. A key prediction of the theory that financial frictions drive our results is that controlling for financial constraints, there is less heterogeneity in monetary policy sensitivity across age. To examine this, we consider two proxies for the degree of financial constraints: a collateral-based measure and a cashflow-based measure (Lian and Ma, 2020, Drechsel, 2023). For the former, we check whether the inclusion of firm leverage, measured as the ratio of total debt to total assets at period $t-1$, interacted with the monetary policy shock changes the results. For the latter, we include an interaction of the monetary policy shock with the ratio of total debt to EBITDA at period $t-1$. For both regression extensions, the larger sensitivity of investment along age persists (see Figures G.5 and G.6 in Appendix G.1).

Figure 12. Differences in debt response along age relative to the youngest group at $h = 1$.

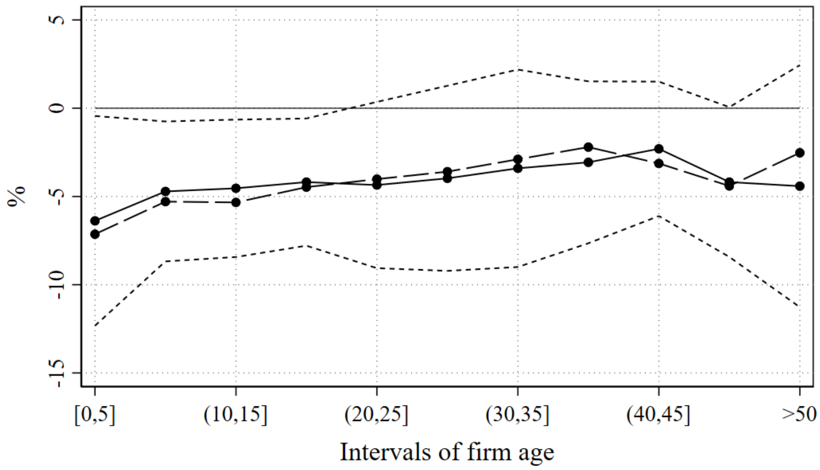


Note: The figure shows the differences in debt responses along age groups relative to the youngest group to a 25*bps* monetary policy tightening shock. The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total debt (short-term debt plus long-term debt) between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 1$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The light gray (dark gray) bars show the 90% (68%) confidence interval. The confidence intervals are based on two-way clustered standard errors by firm and year-month.

Another prediction of the theory that financial frictions drive our results is that the debt of younger firms is also more sensitive to monetary policy than the debt of older firms. Figure 12 shows the differences in the impulse response estimates of debt to a contractionary monetary policy shock for all age groups relative to the youngest group.[22] The plot reveals that the differences between the responses of medium to older firms and the youngest firms are not statistically significant, and the difference between the response for the second youngest age group and the youngest group is only statistically significant at the 68%-level. This speaks

[22] Figures G.3 and G.4 in Appendix G.1 show the average response of debt and the responses across age groups, respectively. Since the average debt response reaches a trough at $h = 1$, the estimations across age are performed at $h = 1$.

Figure 13. Investment response along age groups at $h = 3$ (subsample of firms issuing share capital).



Note: The figure shows the response of investment to a 25bps monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on a subsample of firms that issue share capital in period $t-1$. The solid line with dots shows the point estimate from the full subsample and the long-dashed line with dots from a smaller subsample with share capital growth above the median in period $t-1$. The dashed lines are the 90% confidence interval from the full subsample. The confidence interval is based on two-way clustered standard errors by firm and year-month.

against the hypothesis that our results are driven by differences in the sensitivity of debt across age groups.

Last, we inspect the investment response to monetary policy among a subsample of firms that are less likely to be financially constrained. We find the same patterns as in the baseline estimation. This supports our theory that investment frictions, which operate independently of the financial health of a firm, drive our results. Specifically, a proxy for whether firms are financially constrained that is often used in the literature is whether a firm issues dividends (see, e.g., Albuquerque and Hopenhayn (2004), Begenau and Salomao (2018), Khan and Thomas (2013), Cloyne et al. (2022)). The rationale is that constrained firms would optimally use their earnings to finance growth rather than pay dividends. We do not directly observe dividend payouts in our data. Instead, we approximate it by calculating the growth rate in the financial share capital of firms, where a negative growth rate is equivalent to a dividend issuance. Among the firm-year observations for which we can compute the year-on-year capital growth rate, 89% are negative. The size of these capital reductions is small, however, with a median value of -1.8%.[23] We construct two subsamples comprising *(i)* firms with negative capital growth in the previous period and *(ii)* firms with negative capital growth in the

[23] Previous literature notes that dividend issuances are a persistent state for firms: once a firm issues dividends, it is likely to continue doing so in the future. This is also the case in our sample where 88.4% of observations with capital reductions, i.e., dividend issuance, are followed by further reductions for three or more years.

previous period in excess of the median value of capital reductions. We estimate investment responses to monetary policy shocks on these subsamples. Figure 13 shows the resulting IRFs. Both show a clear gradient in the response of investments along firm age, and the two IRFS are indistinguishable.

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.[24]

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.

[24] 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

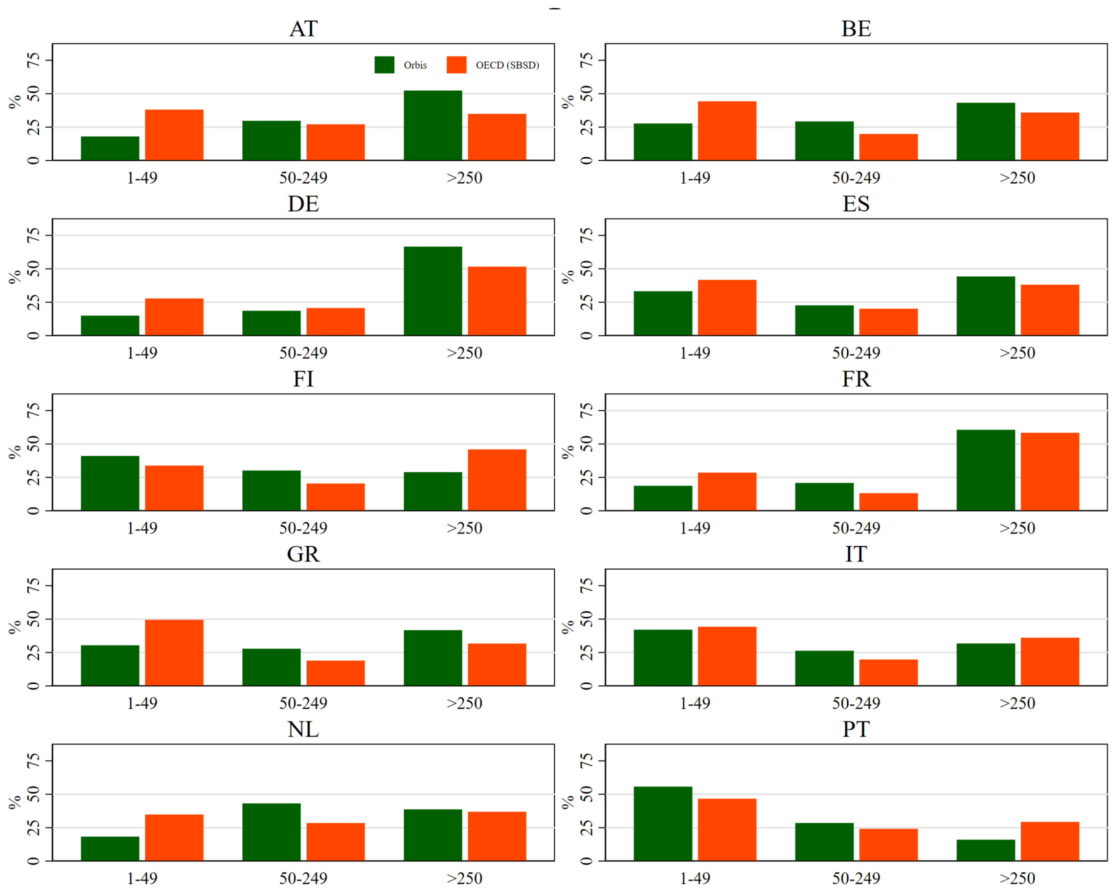
To evaluate the coverage and representativeness of the Orbis data, we follow the exercise presented in Kalemli-Özcan et al. (2019) (see in their paper Table 1 for coverage, Table 2 for representativeness and Appendix C for further details). The comparison is conducted along aggregate "Gross output", 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.

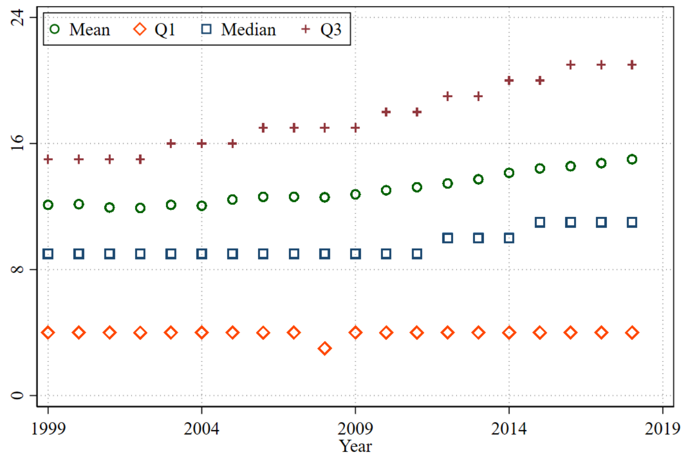
Figure A.1. Representativeness of the firm size distribution based on gross output.



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.

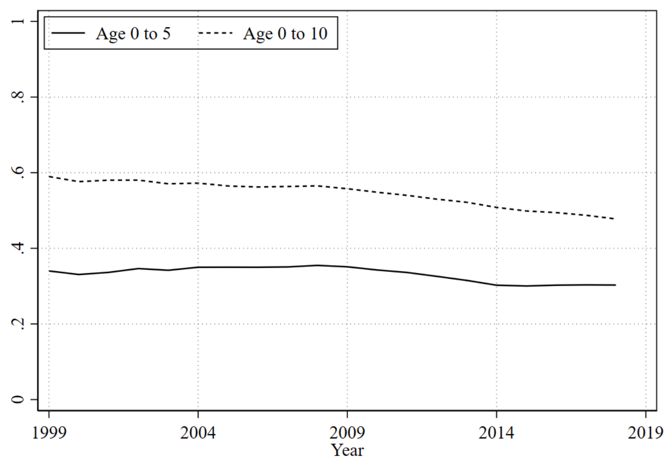
A.3 Additional descriptives

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.

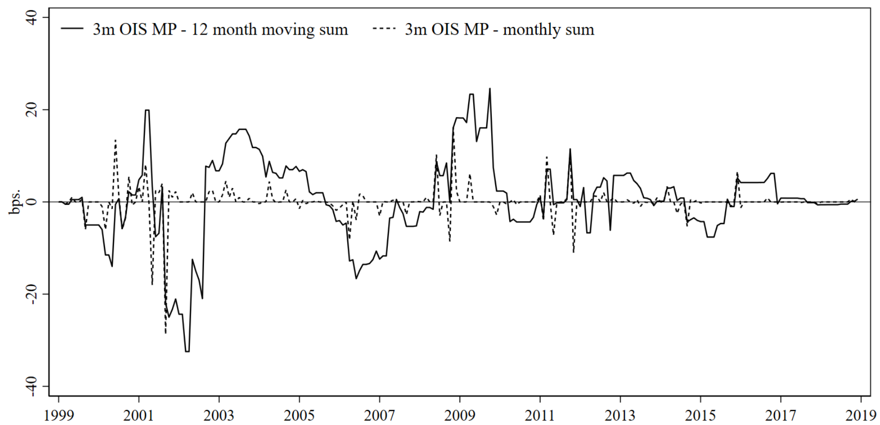


Note: The figure shows the share of sample observations of young firms over time. The solid line is the share of firms of age zero to five and the dashed line is the share of firms of age zero to ten.

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

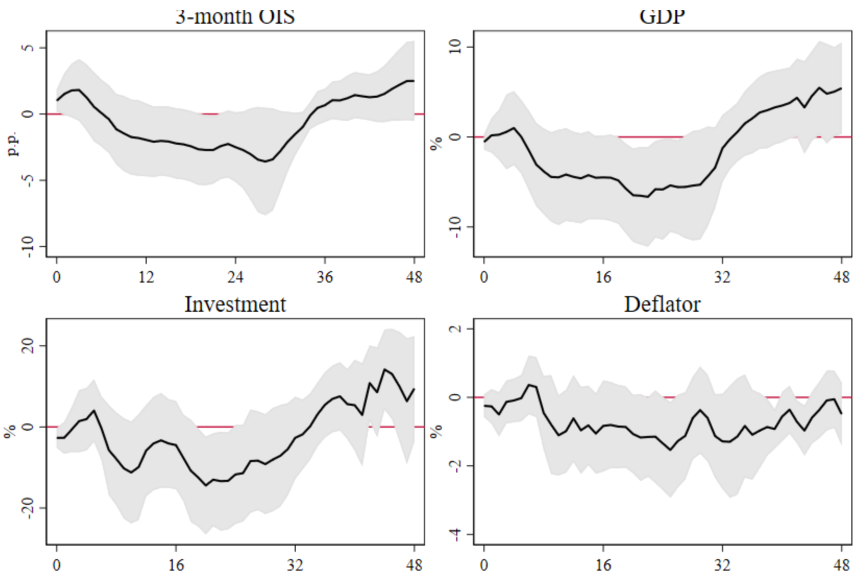
The impulse responses depicted in Figure B.2 are obtained from local projections (Jordà, 2005) estimated on a country panel of the ten euro area countries that are represented in the firm-level data. The estimation equation is given by

$$\Delta_h Y_{j,t+h} = \alpha_{j,h} + \beta_h shock_t^{MP} + \Gamma_h' X_{t-1} + \epsilon_{j,t+h} \tag{8}$$

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.

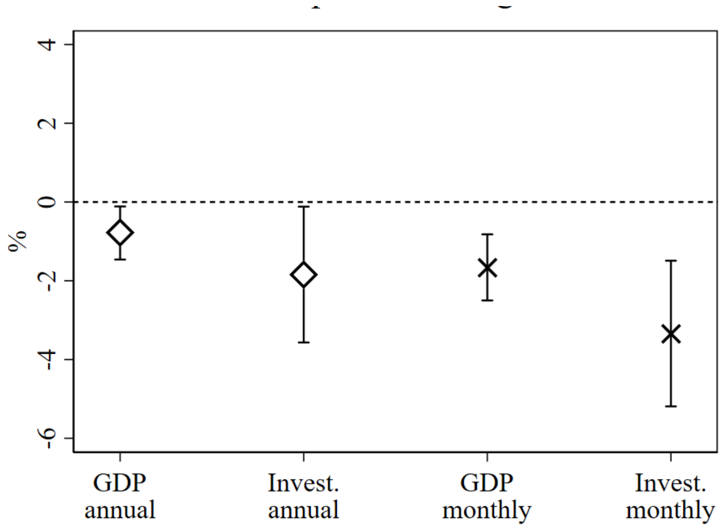


Note: The figure shows impulse response functions from local projections estimated from aggregate data on a panel for ten euro area countries at monthly frequency. The investment series contains investments from all domestic sectors including the government. The responses have been normalized to a 100*bps* 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.

B.3 Validation of aggregation to annual frequency

Figure B.3 shows the trough response of GDP and aggregate investment to a contractionary monetary policy shock at the annual and monthly frequency. The estimates are obtained from the same regression model as detailed in the previous subsection B.2. For the monetary policy shock of the annual responses, all surprises between January and December have been summed up.

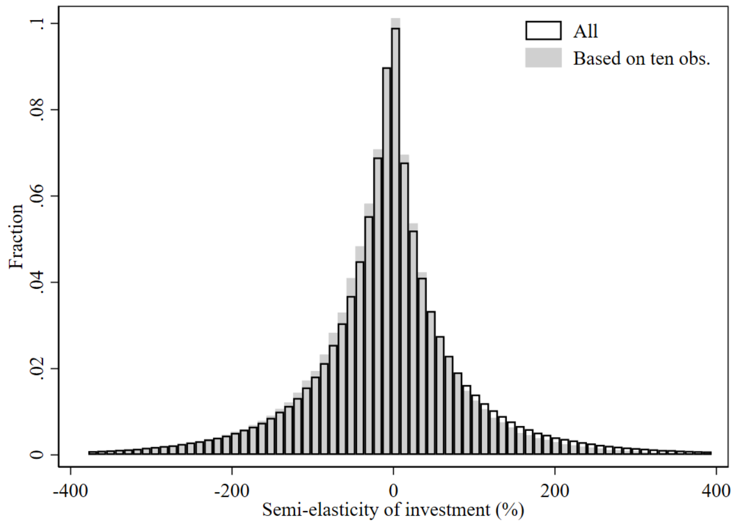
Figure B.3. Trough response of GDP and investment at annual and monthly frequency.



Note: The diamond (x) shows the point estimate at the trough of the impulse response to a MP tightening shock using aggregate data at the annual (monthly) frequency to a 25*bps* increase in the policy rate. The vertical bars show the 68% confidence interval. The estimates are obtained from a panel of ten euro area countries corresponding to those in the firm-level data.

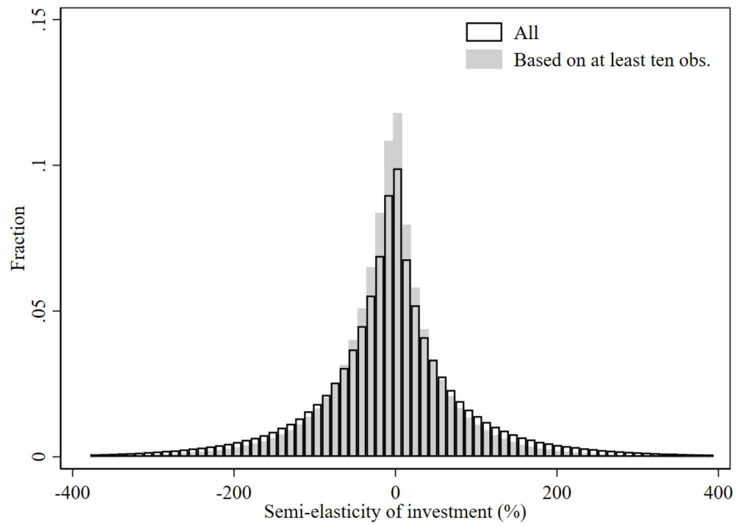
C Investment elasticities

Figure C.1. Histogram of semi-elasticities of investment at $h = 3$ (all firms and firms with ten observations).



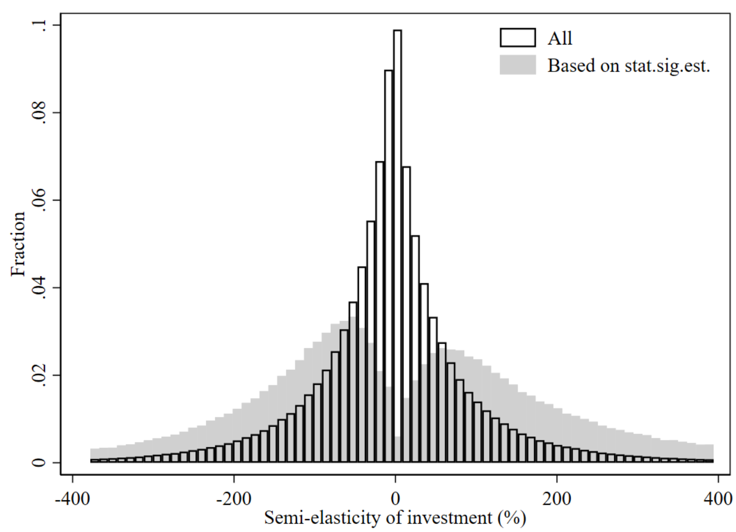
Note: The figure shows the distribution of firm-level semi-elasticities to a 25*bps* contractionary monetary policy shock. The transparent bars show the full set of elasticities that are used for the main analysis. The gray bars show the subsample of elasticities that are estimated for firms with exactly ten observations. The distribution is cut at the top and bottom 1% of the main sample and the number of bins is set to 70. Values outside of $[-100\%, +100\%]$ can be obtained since the change in the capital stock is computed using logs.

Figure C.2. Histogram of semi-elasticities of investment at $h = 3$ (all firms and firms with at least ten observations).



Note: The figure shows the distribution of firm-level semi-elasticities to a 25*bps* contractionary monetary policy shock. The transparent bars show the full set of elasticities that are used for the main analysis. The gray bars show the subsample of elasticities that are estimated for firms with at least ten observations. The distribution is cut at the top and bottom 1% of the main sample and the number of bins is set to 70. Values outside of $[-100\%, +100\%]$ can be obtained since the change in the capital stock is computed using logs.

Figure C.3. Histogram of semi-elasticities of investment at $h = 3$ (all firms and statistically significant elasticities).



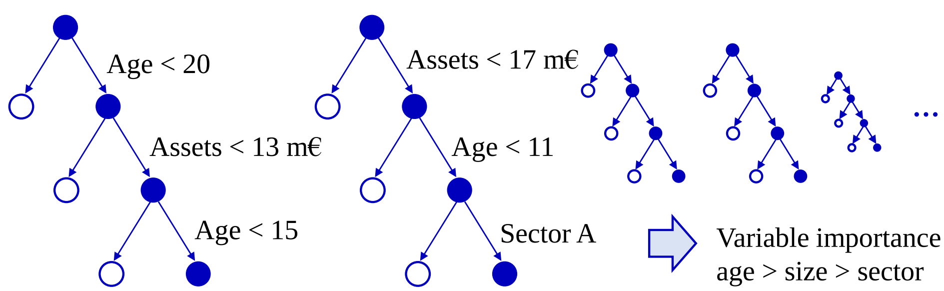
Note: The figure shows the distribution of firm-level semi-elasticities to a 25*bps* contractionary monetary policy shock. The transparent bars show the full set of elasticities that are used for the main analysis. The gray bars show the subsample of elasticities that are statistically significant at the 10% level. The distribution is cut at the top and bottom 1% of the main sample and the number of bins is set to 70. Values outside of $[-100\%, +100\%]$ can be obtained since the change in the capital stock is computed using logs.

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 potential explanatory variables

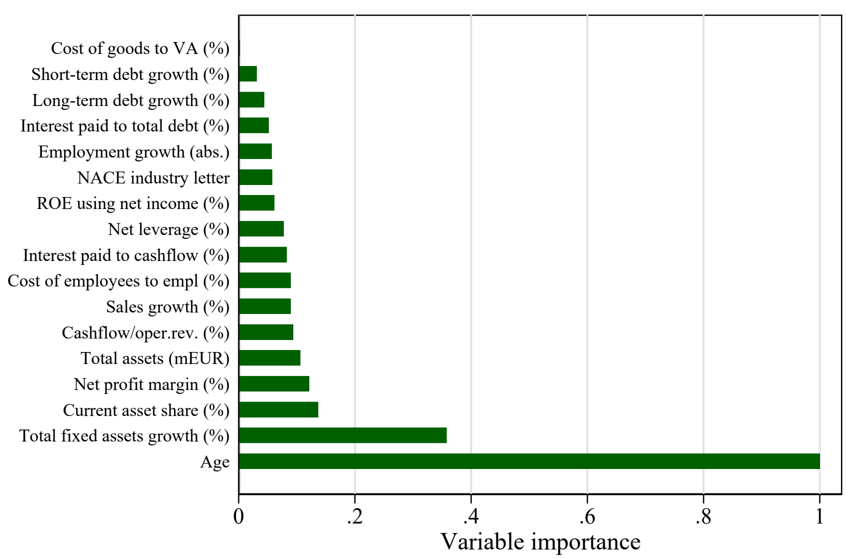
The following list specifies the set of explanatory variables $\bar{\mathbf{X}}_i$ that are considered in the Random Forest algorithm described in subsection 4.2. For all time-varying variables, the time-average over all observations for firm i has been calculated to map them into a single firm-level 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

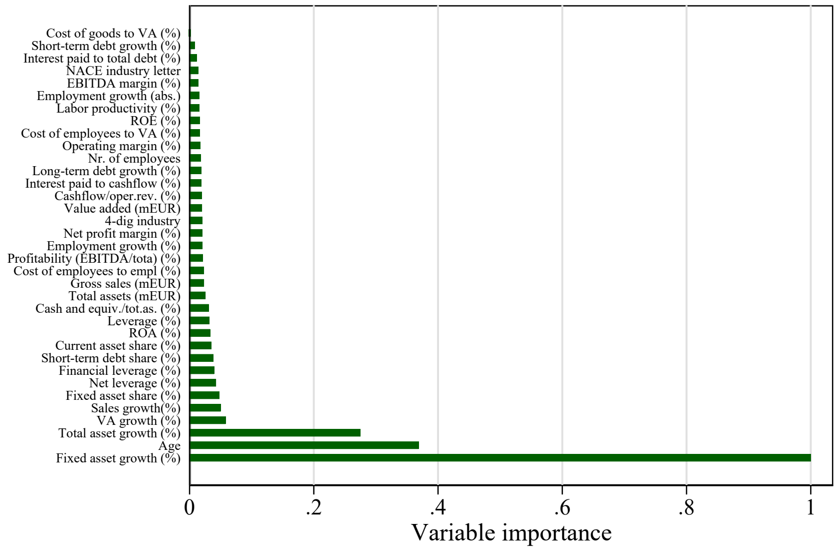
D.3 Random forest on alternative subsamples and covariates

Figure D.2. Variable importance of the semi-elasticity of investments (smaller set of covariates).



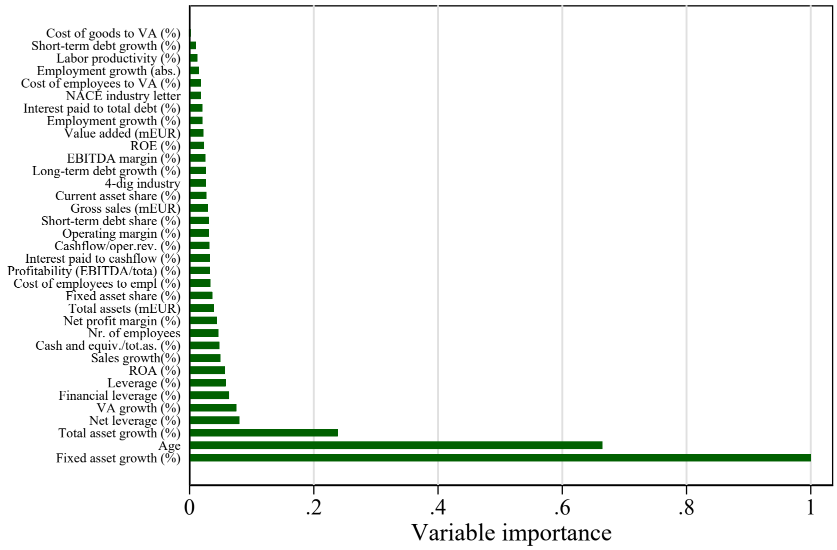
Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of investment to monetary policy estimated from equation (3) at $h = 3$. The set of potential explanatory variables is listed along the left side of the chart. "VA" stands for value added. Covariates that show a high degree of correlation with other covariates have been excluded. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

Figure D.3. Variable importance of the semi-elasticity of investment (subset of elasticities estimated from ten firm-level observations).



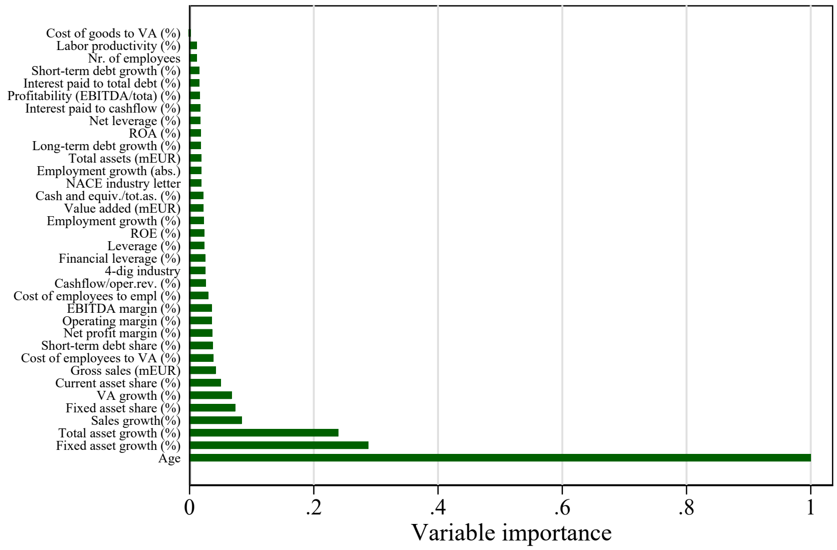
Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of investment to monetary policy estimated from equation (3) at $h = 3$. The set of elasticities is restricted to those that are estimated based on ten firm-level observations. The set of potential explanatory variables is listed along the left side of the chart. “VA” stands for value added. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

Figure D.4. Variable importance of the semi-elasticity of investment (subset of elasticities estimated from at least ten firm-level observations).



Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of investment to monetary policy estimated from equation (3) at $h = 3$. The set of elasticities is restricted to those that are estimated based on at least ten firm-level observations. The set of potential explanatory variables is listed along the left side of the chart. "VA" stands for value added. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

Figure D.5. Variable importance of the semi-elasticity of investment (subset of statistically significant elasticities).

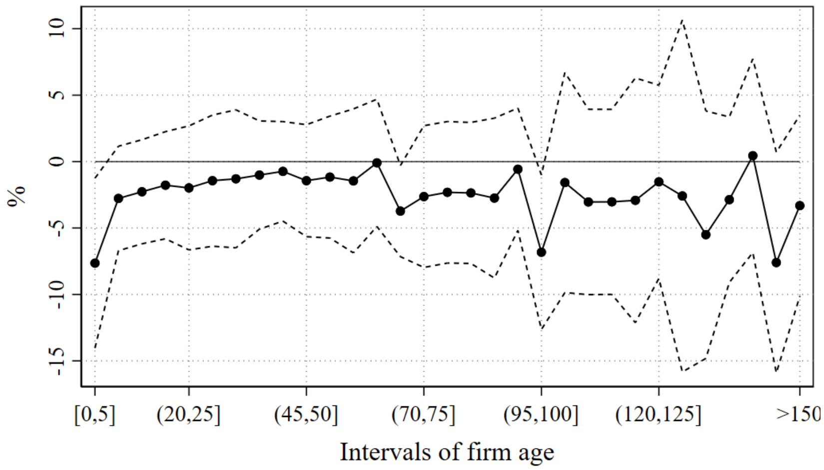


Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of investment to monetary policy estimated from equation (3) at $h = 3$. The set of elasticities is restricted to those that are statistically significant at the 10% level. The set of potential explanatory variables is listed along the left side of the chart. "VA" stands for value-added. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

E Additional charts main findings

E.1 Baseline

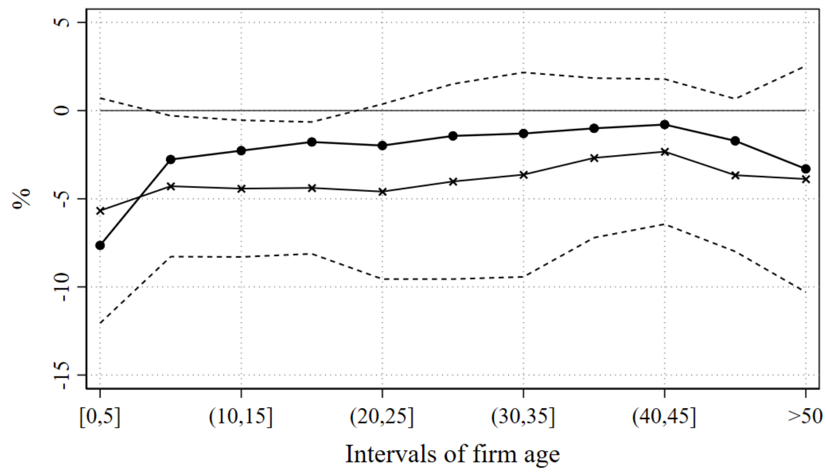
Figure E.1. Investment response along age groups at $h = 3$ (extended to age 150).



Note: The figure shows the response of investment to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than one hundred fifty. The dashed line is the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

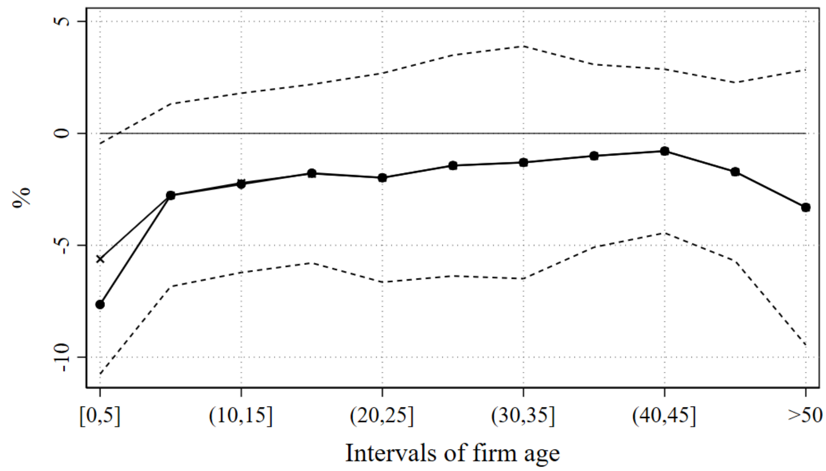
E.2 Robustness

Figure E.2. Investment response along age groups at $h = 3$ (robustness: exclude exiting firms).



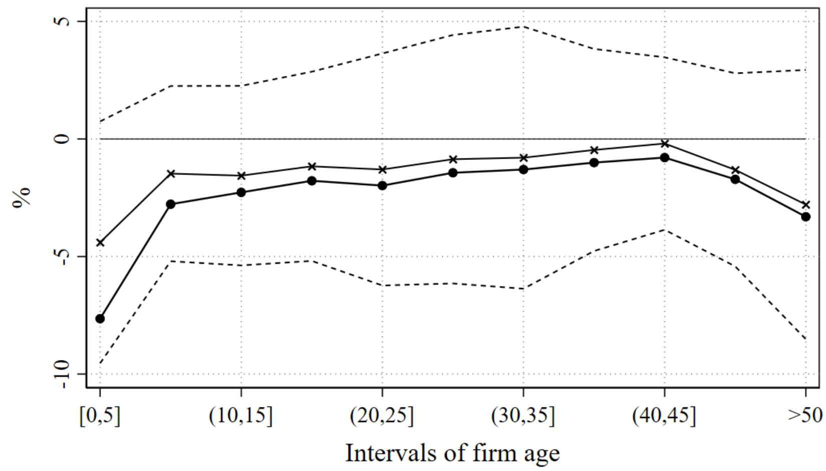
Note: The figure shows the response of investment to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on a subsample of firms that do not exit throughout the IRF horizon of four years. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

Figure E.3. Investment response along age groups at $h = 3$ (robustness: exclude entrants).



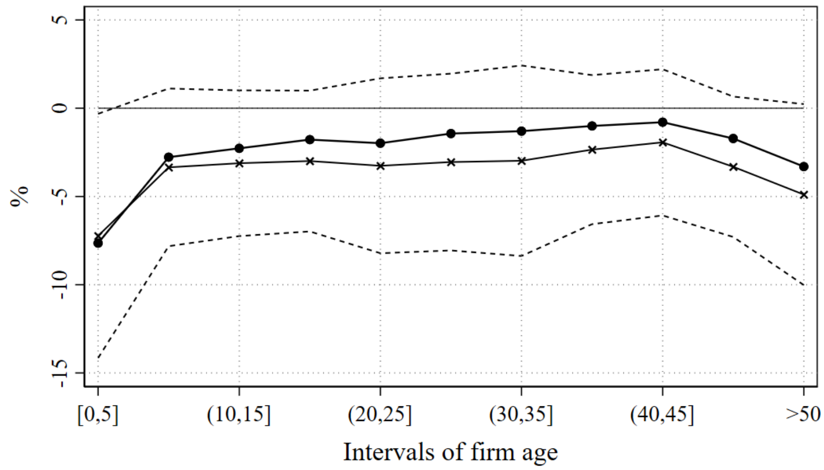
Note: The figure shows the response of investment to a 25bps monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on a subsample of firms that are at least three years old at the time of the monetary policy shock, i.e., excluding entrants. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

Figure E.4. Investment response along age groups at $h = 3$ (robustness: controlling for firm size).



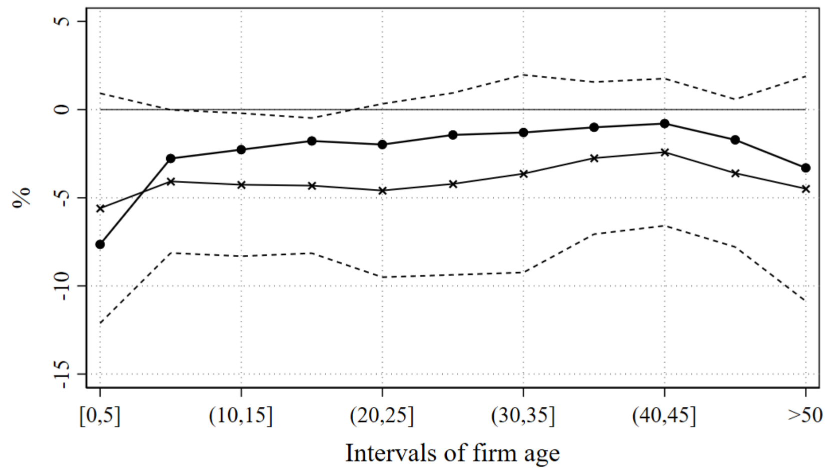
Note: The figure shows the response of investment to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on an extension of the baseline regression, which also includes an interaction of the monetary policy shock with a lagged firm size measure (log of total assets) as well as the level of that variable. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

Figure E.5. Investment response along age groups at $h = 3$ (robustness: subsample through 2011).



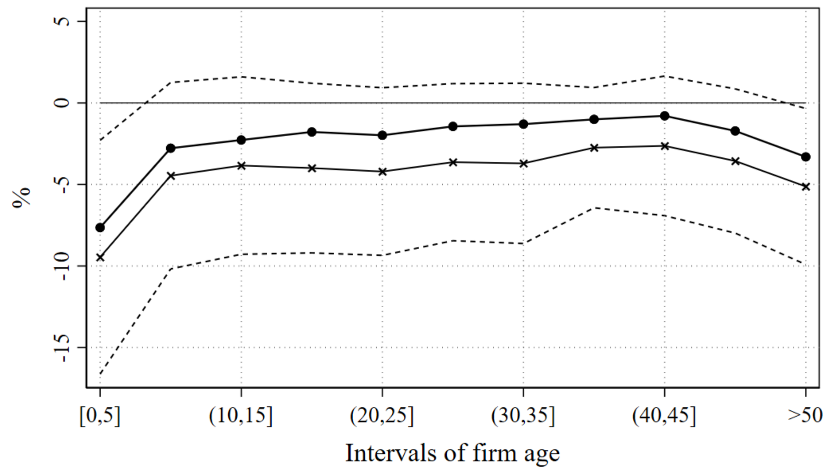
Note: The figure shows the response of investment to a 25bps monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on a subsample running through 2011. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

Figure E.6. Investment response along age groups at $h = 3$ (robustness: subsample through 2013).



Note: The figure shows the response of investment to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on a subsample running through 2013. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

Figure E.7. Investment response along age groups at $h = 3$ (robustness: shadow rate).



Note: The figure shows the response of investment to a $25bps$ monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on an extension of the baseline regression, which also includes a lagged shadow rate measures. The construction of that variable is detailed in the main text. The solid line with x-markers shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with dots shows the point estimates from the baseline estimation.

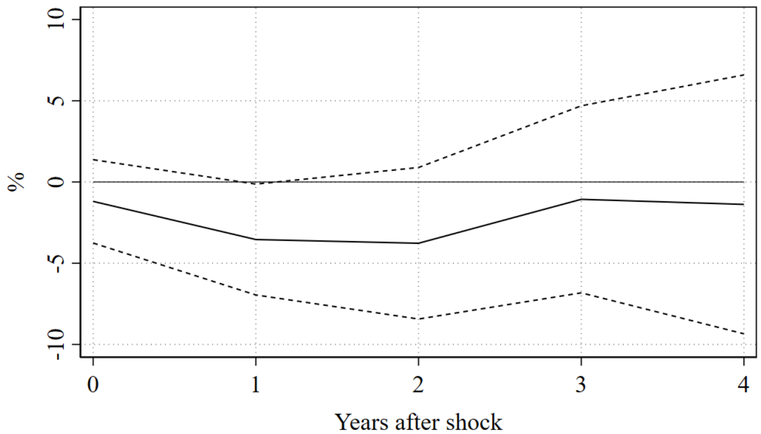
F Findings for employment

Another important variable to consider when studying monetary policy transmission to firms is employment. Analogous to the main part of the paper, this Appendix section investigates predictors for heterogeneous responses of employment to monetary policy. This analysis is not conclusive, however, and further work is needed to gain additional insights.

Figure F.1 shows the average response of employment to a contractionary monetary policy shock estimated from the full sample of firms. It shows that an increase in the interest rate leads to a fall in employment with a trough of -3.8% after two years. To detect heterogeneity along firm characteristics, we again start by estimating the semi-elasticity of employment for each firm in the sample and subsequently use the elasticities as outcome variable in a Random Forest to detect observables that are important for explaining their variation. In line with the timing of the trough in the average response, we consider the elasticities at $h = 2$. Figure F.2 shows the output from that exercise. Like in the case of investment elasticities, firm age is indicated as most important variable. This time, however, there are other variables that also appear to be important and the distance between the most important variable and the rest is relatively small. The second most important variable is the industry where a firm operates and the third most important the ratio of the wage bill to the number of employees.

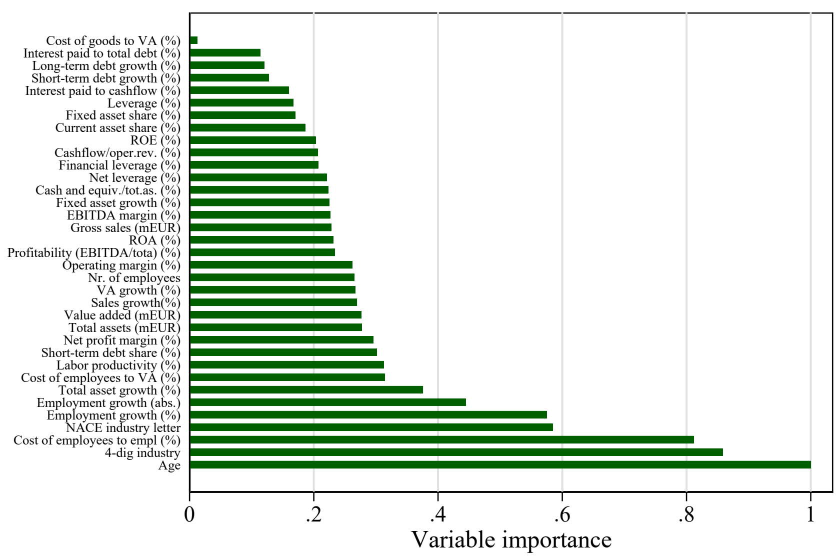
Figure F.3 shows the impulse responses at $h = 2$ along firm age. The youngest group with firms up until age five shows the largest decline in employment, however, the confidence interval for that group is very wide. From the second group onward the gradient in the response for the different age groups becomes flat and there is no clear pattern of heterogeneity along age alone. This could relate to the fact that there are other variables of importance, as indicated in the Random Forest exercise. A way forward from here could be to further split the data and estimate the impulse responses along age separately for firms in different industries as well as firms with a varying degree of labor costs relative to the number of employees.

Figure F.1. Average employment response.



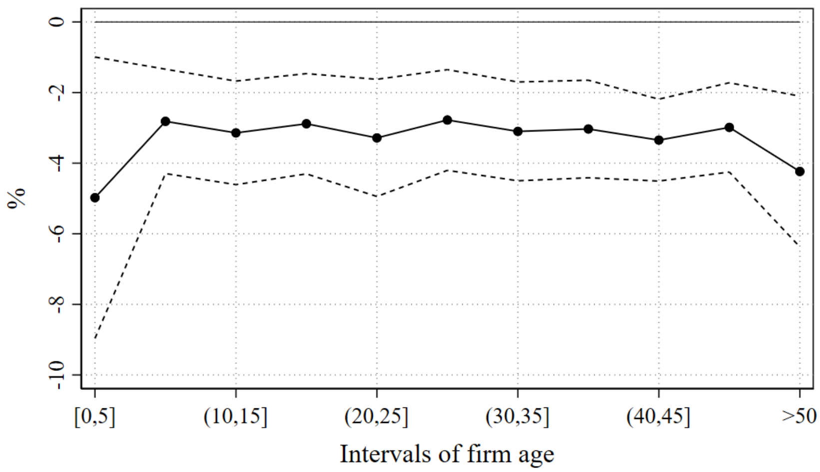
Note: The figure shows the response of employment to a 25bps monetary policy tightening shock as per equation (1). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in employment between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon h shown along the x-axis. The dashed line shows the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

Figure F.2. Variable importance of the semi-elasticity of employment.



Note: The figure shows the variable importance from the Random Forest. The outcome variable is the firm-level semi-elasticity of employment to monetary policy estimated from equation (3) at $h = 2$. The set of potential explanatory variables is listed along the left side of the chart. A detailed list of all explanatory variables is provided in Appendix D.2. The scale of the most important variable is normalized to one.

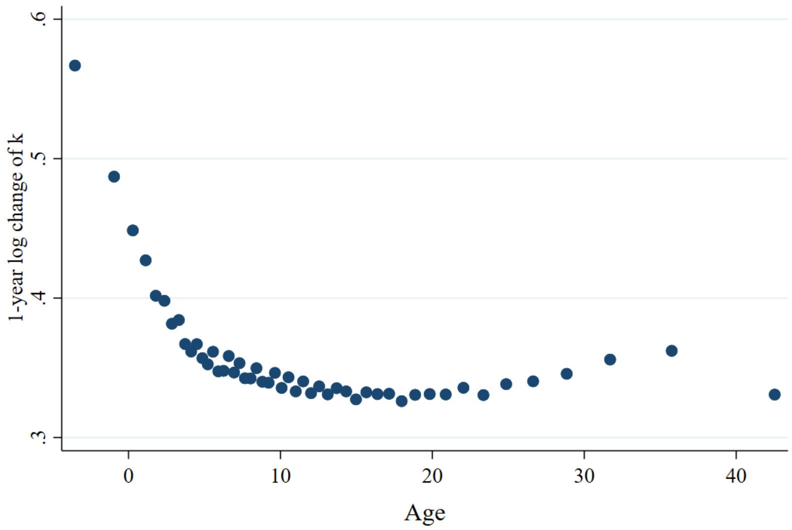
Figure F.3. Employment response along age groups at $h = 2$.



Note: The figure shows the response of employment to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in employment between period $t - 1$ and $t + h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 2$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimates are from separate regressions for each group. The dashed line is the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

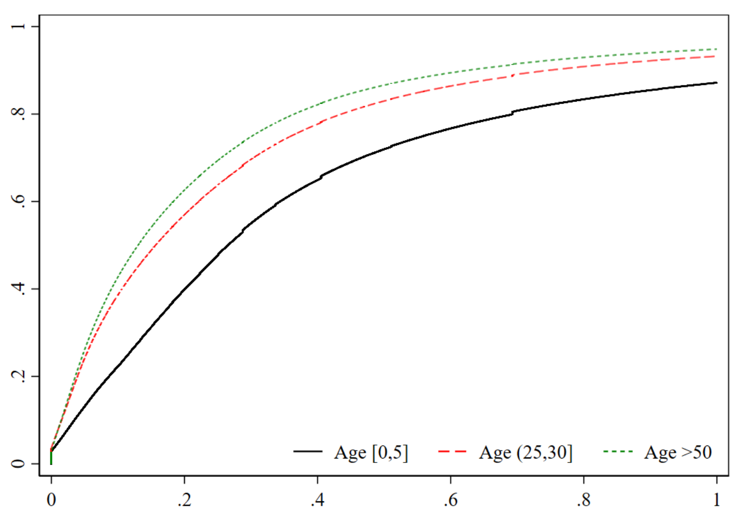
G Model predictions in data

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



Note: The figure shows a binscatter plot of the one year growth rate in fixed assets across firm age after controlling for firm size. The dots are the median positive growth rate by age. The growth rate is in percent of the stock of fixed assets in the previous year. Firm size is measured as the log of total assets in the previous period.

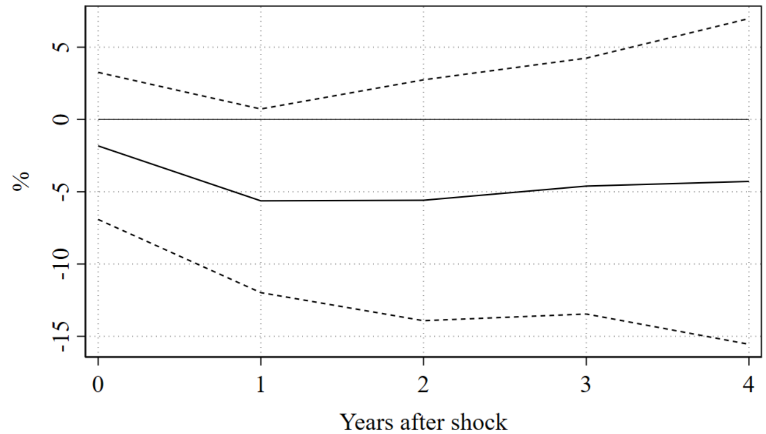
Figure G.2. CDF of fixed asset growth across age groups.



Note: The figure shows the cumulative distribution function of absolute unconditional changes in total fixed assets over one year. The distribution is plotted for three groups of firm age: firms that are at most five years old (black solid line), between twenty-five and thirty years of age (red dashed line) and older than fifty years (green dotted line). The values are cut at one (100%).

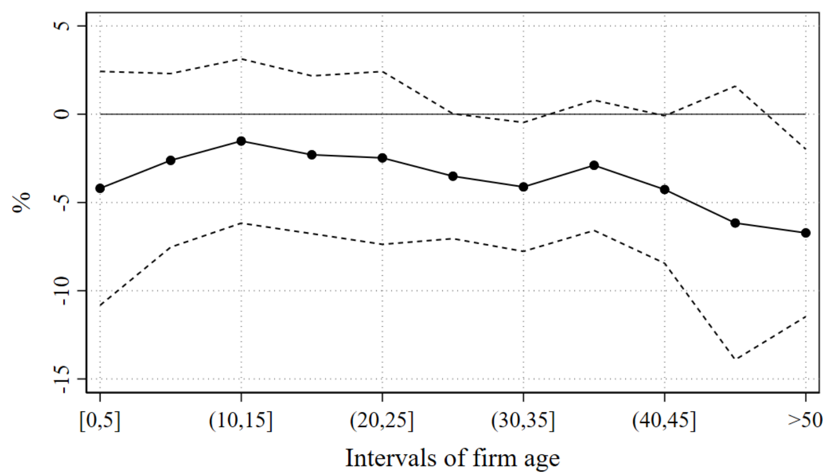
G.1 Tests for financial frictions

Figure G.3. Average debt response.



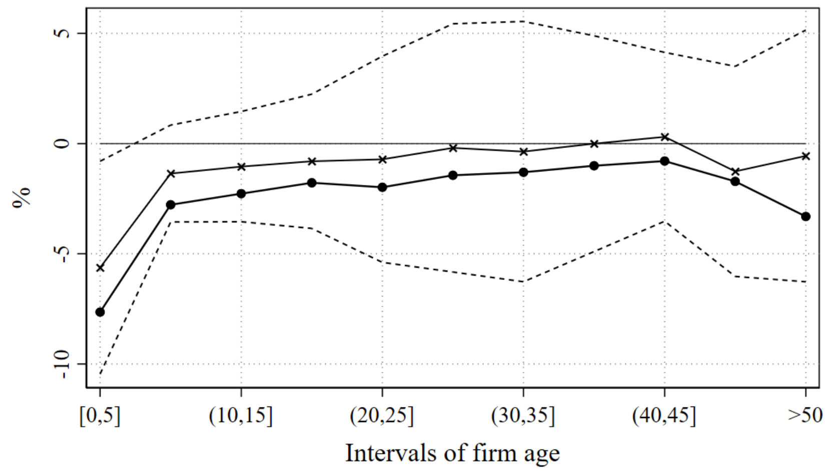
Note: The figure shows the response of debt to a 25*bps* monetary policy tightening shock as per equation (1). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in debt (short-term debt plus long term-debt) between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon h shown along the x-axis. The dashed line shows the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

Figure G.4. Debt response along age groups at $h = 1$.



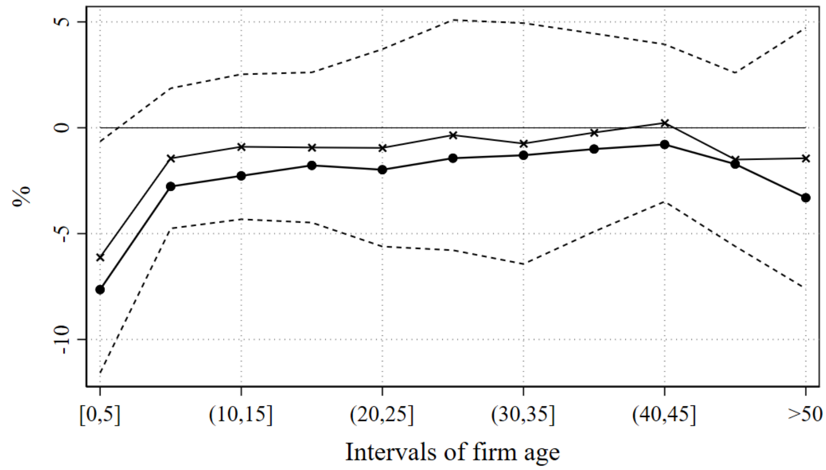
Note: The figure shows the response of debt to a 25*bps* monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in debt (short-term debt plus long-term debt) between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 1$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The dashed line is the 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month.

Figure G.5. Investment response along age groups at $h = 3$ (controlling for leverage ratio).



Note: The figure shows the response of investment to a 25bps monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on an extension of the baseline regression, which also includes an interaction of the monetary policy shock with a lagged collateral-constraint measure (total debt to total assets) as well as the level of that variable. The solid line with dots shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with x-markers shows the point estimates from the baseline estimation.

Figure G.6. Investment response along age groups at $h = 3$ (controlling for debt-to-EBITDA ratio).



Note: The figure shows the response of investment to a $25bps$ monetary policy tightening shock along firm age as per equation (2). The dependent variable $\Delta_h Y_{i,t+h}$ is the cumulative log-change in total fixed assets between period $t-1$ and $t+h$ with the monetary policy shock dated at t and the projection horizon is fixed at $h = 3$. Firms are grouped according to their age at time t and each group contains five years of age except for the first group, which also includes age zero and the last which includes all observations of firms older than fifty. The estimation is based on an extension of the baseline regression, which also includes an interaction of the monetary policy shock with a lagged cashflow-constraint measure (total debt to EBITDA) as well as the level of that variable. The solid line with dots shows the point estimate from that estimation. The dashed lines are the corresponding 90% confidence interval. The confidence interval is based on two-way clustered standard errors by firm and year-month. The solid line with x-markers shows the point estimates from the baseline estimation.