Firm Heterogeneity and Monetary Policy Transmission*

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February 13, 2022

Abstract

This paper studies differences in monetary policy transmission across firms. Using high-frequency identification, I estimate firm-level elasticities of investment to an exogenous change in interest rates. Next, a Random Forest algorithm is employed to investigate which firm characteristics are important for explaining variation in investments. I find that age and size of firms are important observables for transmission heterogeneity and investment responses weaken in both age and size. In contrast, investments of high-growth firms, for any age and size, are not sensitive to monetary policy. I conclude with a discussion of potential mechanisms for rationalizing this finding.

Keywords: Firm heterogeneity, Monetary policy transmission, High-frequency identification, Random Forest, Local Projections

JEL Classification: E22, E44, E52, 016

*I am grateful for invaluable guidance and support by Per Krusell and Timo Boppart during this project and beyond. I also want to thank Gabriel Chodorow-Reich, Veronica de Falco, John Hassler, Fédéric Holm-Hadulla, Karin Kinnerud, Kieran Larkin, Jeremy Stein, Ludwig Straub, Adi Sunderam, Lina Thomas, Joshua Weiss, as well as seminar participants at the IIES and the Harvard/HBS Finance Lunch for helpful comments and suggestions.

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1 Introduction

Based on the findings on the financial accelerator (Bernanke et al., 1999, Kiyotaki and Moore, 1997, Holmstrom and Tirole, 1997), it has been well established that firms are differentially affected by financial constraints. Since monetary policy is a relevant source for aggregate fluctuations that shifts around these financial constraints, it is important to deepen the understanding about which characteristics make firms more or less responsive to changes in central bank rates. Moreover, in the vein of the "micro-to-macro" analysis (see e.g., Nakamura and Steinsson (2014), Carvalho et al. (2020), Chodorow-Reich et al. (2021)), this can also lead to a better understanding of the composition of the well-studied aggregate effects of monetary policy.

Motivated by these questions, this paper investigates heterogeneity in monetary policy transmission to firms. My analysis uses a large firm-level data set together with high-frequency identified monetary policy shocks, in order to gain insights on these questions. Starting from firm-level estimates of investment elasticities to exogenous change in interest rates, I employ a Random Forest algorithm (Breiman, 2001) to identify which firm characteristics are important for explaining variation of investments for firms with high and low elasticities. I find that age and size of firms are important observables for transmission heterogeneity. Next, I estimate impulse responses using Jordà (2005)'s local projection method in order to quantify these differences. For younger and smaller firms, there is a clear reduction in investments in response to monetary policy tightening and the investment response becomes weaker as age and size increase. In contrast, investments of high-growth firms are not sensitive to monetary policy, for any age and size.

These findings could be indicative of various underlying mechanisms. First, there could be reallocation across firms due to monetary policy, with resources shifting from low productivity to high productivity (most likely high-growth) firms. This shift of resources could explain why the high-growth firms do not show any change in investment when monetary policy adjusts. A second potential mechanisms could be that high-growth firms have better investment opportunities, which allows them to make their investment decisions independent of the aggregate financial conditions shaped by monetary policy. Third, these findings could be indicative of earnings-based constraints. Since high-growth firms might experience stronger earnings and positive cashflows, the presence of such borrowing constraints could explain why investment decisions of these firms are not responsive to monetary policy in the way that the broad set of firms is. In the continuation of the empirical analysis, I intend to identify which of these hypotheses most likely explains the results. Once this is established, I will develop a model of heterogeneous firms that can shed further light into the underlying mechanisms and transmission channels.

This paper is also informative about the challenges to monetary policy during the post-pandemic recovery for various reasons. First and foremost, it can contribute to the understanding of differences in transmission across firms and in particular for high-growth firms. These firms play an important role for the generation of employment over the business cycles as well as the accumulation of productivity and creation of innovation, which are crucial for long-term economic growth. In particular, the post-pandemic recovery will be accompanied by a stark shift in the monetary policy stance, from a long period of monetary policy stimulus to tightening of financial conditions. Against this background it appears highly relevant for policy makers to be aware of heterogeneous effects of their policies for this important group of firms. In addition, smaller private firms might face more difficulties in recovering from the economic downturn caused by the pandemic as they, e.g., have less stable and diverse access to sources of external finance. Since this project works with a data set that primarily includes such firms, the insights from the analysis can be especially relevant for understanding the responses of these particular firms to monetary policy.

Related literature. This paper provides additional insights for to two broad branches of the literature. First, it relates to previous studies that look at monetary policy transmission along different firm characteristics. For this purpose, various firm characteristics have been taken into account, such as firm age (Durante et al., 2020, Cloyne et al., 2018), size (Kashyap et al., 1996, Crouzet and Mehrotra, 2020), bank dependence (Crouzet, 2021, Holm-Hadulla and Thürwächter, 2021) as well as balance sheet characteristics such as firm leverage and liquidity positions (Ottonello and Winberry, 2020, Jeenas, 2019, Auer et al., 2021). My paper adds to these findings in three ways. First, by employing a Random Forest algorithm, I take an agnostic data-driven approach to identifying the most important source for transmission heterogeneity across firms. Then, I further look into the subset of firms, which experiences high-growth, which is a dimension of heterogeneity that has not been studied in the context of monetary policy. Moreover, my dataset consists of a very broad set of firms along the age and size distribution, and thus lends itself to further studying these high-growth firms, which are often young and small.

In addition, the paper also relates to studies of firm dynamism and the role of financial conditions (see, e.g., Barlevy (2003), Huber (2018), Dinlersoz et al. (2019), Kochen (2022)). As a novelty relative to these papers, my analysis focuses on monetary policy as a specific source of aggregate financial fluctuations.

The following Section 2 describes the underlying firm-level data as well as the identification approach to monetary policy. Subsequently, Section 3 lays out the empirical methods used and the results are presented in Section 4. I discuss potential mechanisms that could explain the findings in Section 5 and Section 6 concludes.

2 Data and identification

The first subsection 2.1 presents some information on the firm-level data as well as key characteristics of the sample. Subsequently, subsection 2.2 discusses the identification of exogenous monetary policy shocks and gives more details on the data used for identification in this paper.

2.1 Firm-level data

The firm-level data is from the Orbis database by Bureau van Dijk, which contains panel data of private and public firms. My sample consists of 8.4 million non-financial firms from ten euro area countries over the time period 1999 to 2018.[1] The data frequency is annual and I 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, I closely follow the detailed guidance by Kalemli-Özcan et al. (2019) as well as some additional cleaning steps as outlined by Durante et al. (2020). Last, I perform manual data checks and cleaning along all variables for some of the largest and smallest observations in the sample.

Overall, the sample has a very good coverage of the aggregate economies and the distribution of firms by size is representative of the aggregate firm distribution. When summing up gross sales across all firms in the sample for each year, the coverage is larger than 60% for most countries and for some even as high as 80% (see Table A.1 in Appendix A for the aggregated gross output shares across countries and time). In addition, the distribution of firms in terms of size by em-

[1] 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. 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.

ployment is close to the aggregate firm distribution in the respective countries. When calculating the share of firms in the Orbis sample that fall into a certain size bin and comparing that to the share of firms along size in the aggregate, we can see that these two line-up well with some variation across countries (see Figure A.1 in Appendix A for details).

Table 1 shows some key summary statistics of the sample, which reveal three takeaways.[2] First, the number of observations is very large. In particular, the balance sheet variables are available for most firms amounting to almost 64 million firm-year observations for total assets. Also, the income statement contains a lot of observations, here represented by gross sales, and the number of employees is available for more than half of the firm-year observations in the sample. Importantly, the date of corporation from which firm age is computed, is almost always available. Second, looking across the percentiles and up to the maximum observation, the distribution of firms is very wide. While the average firm has around 5 m€ in total assets and is around 14 years of age, the largest and oldest firm are significantly larger and older.[3] Third, the majority of firms is relatively small and young. At the median, the firm size in terms of total assets is only around 0.3 m€ and even at the 90*th* percentile, the size is only about 3.3 m€. Similarly, the median firm is ten years old and the vast majority of firms is not more than 30 years old.

Table 1: Summary statistics.

	N	Mean	p10	p50	p90	Max
Total assets (m€)	63,896,414	4.82	0.03	0.29	3.26	245,847.83
Gross sales (m€)	42,975,016	4.92	0.02	0.34	4.15	154,587.80
Number of employees	34,099,300	20.56	1	4	30	323,298
Firm age	63,837,091	13.59	2	10	29	901

Note: Total assets and gross sales have been deflated using the GDP deflator of the respective country with base year 2015.

2.2 Monetary policy shocks and identification

The monetary policy shocks are identified using high-frequency surprises in short-term interest rates around Governing Council meetings (e.g., Kuttner (2001), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Altavilla et al. (2019) as well as Ramey (2016) for a discussion on this identification

[2] In Appendix A, I specify all firm-level as well as macro-level data series and their transformation, where applicable, for the analysis in this paper.

[3] 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.

approach). The identifying assumption is that changes in interest rates over a narrow window around the policy decision are solely attributed to monetary policy and not reflective of changes in aggregate conditions. I 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).[4] In my analysis, I consider the surprises in the 3-month OIS calculated over the entire event window, i.e., from before the press release to after the press conference.

Following Jarocinski and Karadi (2020), I use only surprises from events where interest rates and stock prices move in opposite directions.[5] 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 classic 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 and thus company valuations going forward. 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 policy makers possesses 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.

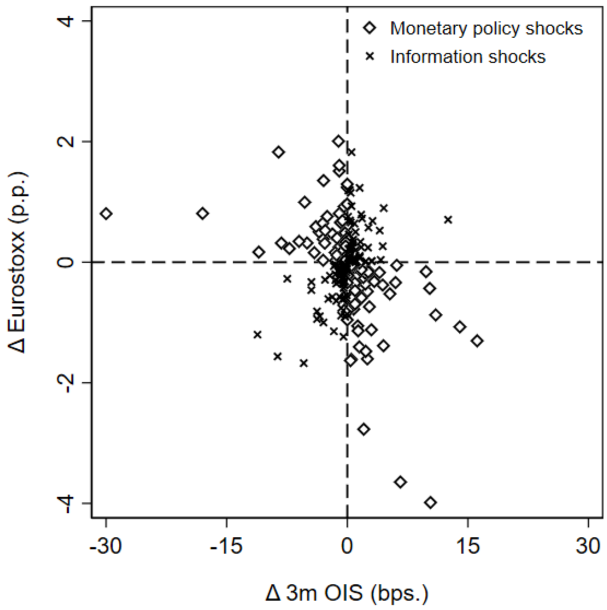
Figure 1 shows all surprises in the 3-month OIS rate plotted against the concurrent changes in the stock market index. In accordance with the previous elaborations, my analysis considers only events where the two asset prices have a negative correlation, namely those located in the second and the forth quadrant. To match the firm-level data I aggregate the surprises to the annual frequency. In order to validate the aggregation of the shocks, I follow Holm et al. (2021) and compare IRFs to macro variables that are available on the monthly and the annual frequency. This exercise confirms both the magnitude and dynamics of transmission across frequencies. As a robustness exercise, I confirm that my findings hold through when using time-weighted shocks (see subsection 4.4).[6]

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

[5] Other examples of 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.

[6] Figure B.1 in Appendix B shows a time series plot of all the shocks considered in the paper.

Figure 1. Stock price and policy rate surprises.



Note: Surprises marked with a cross (first and third quadrant) are referred to as information shocks and surprises marked with a diamond (second and forth quadrant) are the pure monetary policy shocks.

3 Empirical methodology

The empirical analysis proceeds in three steps. First, I estimate firm-level investment elasticities to exogenous changes in monetary policy (subsection 3.1). Second, a Random Forest algorithm is employed to identify the relevant firm characteristics for differences in investments for firms of high and low sensitivity (subsection 3.2). Last, subsection 3.3 describes how the dynamic response to monetary policy shocks across different groups of firms is estimated.

3.1 Investment elasticities

I estimate investment elasticities by running firm-by-firm regressions as given in equation (1)

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \beta_{i,h} shock_t^{MP} + \Gamma'_{i,1} X_{t-1} + v_{i,t+h} \tag{1}$$

where the dependent variable is defined as $\Delta_h Y_{i,t+h} = \left(\frac{TFAS_{t+h} - TFAS_{t-1}}{TFAS_{t-1}}\right)$ and measures cumulative investment in total fixed assets (TFAS) over h-periods. $\alpha_{i,h}$ is an intercept and X_{t-1} is a vector of lagged macro-level controls, comprised of real GDP growth of the country where firm i is located and the short-term risk-free rate. The regression coefficient $\hat{\beta}_{i,h}$ measures the elasticity of investment of firm i to changes in monetary policy.

3.2 Random Forest

In order to establish which observables explain differences in $\hat{\beta}_{i,h}$ across firms, I resort to an agnostic data-driven procedure and employ a Random Forest. The aim of the algorithm is to identify sample splits along which the variation in the outcome variable is maximised. Since the elasticities $\hat{\beta}_{i,h}$ are estimated from variation along the time-dimension, which is at most twenty years, they turn out rather noisy and their numerical values may be interpreted with caution. Hence, instead of using $\hat{\beta}_{i,h}$ as the outcome variable in the algorithm, I proceed in a more indirect way. First, I group firms into two groups, low and high elasticity firms, based on $\hat{\beta}_{i,h}$. Then, I run the Random Forest with the actual cumulative investment as an outcome variable for both groups and compare which of the potential explanatory variables are more important in one and less important in the other group. As an input to the algorithm, I define a set of 25 potential firm characteristics (size, sector, age, debt structure, capital structure, profitability, growth etc.) that could explain differences in transmission across firms. They are listed in Appendix C. The outcome of the algorithm is a relative ranking of the importance of these characteristics in explaining the outcome variability.

Importantly, this procedure has two key advantages. First, it allows for non-linearities between outcome and regressors as well as among regressors, which appear important when studying the transmission mechanism of monetary policy. Second, it does not suffer from the otherwise occurring statistical issues from multiple hypotheses testing. A stylised example of the procedure of the Random Forest is illustrated and discussed in Appendix C.

3.3 Impulse responses

This subsection presents the regression specifications used to derive impulse responses. First, the estimation of the average effect is discussed and subsequently, I present the extension of that baseline regression to estimate heterogeneous responses along different firm characteristics.

Average effect. I estimate impulse response functions (IRFs) using Jordà (2005)'s local projections method as specified in equation (2).

$$\Delta_h Y_{i,t+h} = \alpha_{i,h} + \beta_h shock_t^{MP} + \Gamma'_{1,h} X_{i,t-1} + \Gamma'_{2,h} \bar{X}_t + \Gamma'_{3,h} \tilde{X}_{t-1} + \epsilon_{i,t+h} \tag{2}$$

As in the estimations of elasticities from equation (1), the outcome variable is investments defined as cumulative changes in total fixed assets. Since this is now estimated on the panel, $\alpha_{i,h}$ is a firm fixed effect and $X_{i,t-1}$ includes lagged firm controls in addition to the macro-level controls captured by $\bar{X}_t$ and $\tilde{X}_{t-1}$. Following Ottonello and Winberry (2020), the firm-level controls are the lagged sales growth, firm size, measured by the log of total assets, and the ratio of current assets to total assets. The vector of current macro control variables comprises of real GDP growth and inflation, measured as growth in the GDP deflator, both at the country level and the euro area level. In addition to these variables, the lagged macro controls also contain the short-term risk-free interest rate. The sequence of $\hat{\beta}_h$ coefficients yields the IRF along h. Last, the estimations use Driscoll and Kraay (1998) standard errors, which allow for serial correlation, which is inherent to LPs, as well as spacial dependence across firms.

Transmission across groups. The baseline equation (2) can easily be extended to take into account differences in transmission across firm groups, as shown in equation (3).

$$\begin{aligned}\Delta_h Y_{i,t+h} = \alpha_{i,h} + \sum_{g=1}^{G} \beta_{g,h} \mathbb{1}\left[Z_{i,t} \in g\right] shock_t^{MP} + \sum_{g=1}^{G} \alpha_{g,h} \mathbb{1}\left[Z_{i,t} \in g\right] \\ + \Gamma'_{1,h} X_{i,t-1} + \Gamma'_{2,h} \bar{X}_t + \Gamma'_{3,h} \tilde{X}_{t-1} + \epsilon_{i,t+h}\end{aligned} \tag{3}$$

By including an indicator function $Z_{i,t}$ as well as its interaction with the MP shock, the intercept and the slope of the response are allowed to vary across groups g. The firm-level and macro controls $X_{i,t-1}$, $\bar{X}_t$ and $\tilde{X}_{t-1}$ are as specified before.

For both age and size, I specify two groups and estimate (3) for each of the groups separately.[7] With regard to age, I classify firms into being "young" (age $\leq$ 15) or "mature" (age $>$ 15), which is in line with Cloyne et al. (2018). In terms of size, the two groups are "small- and medium-sized enterprises (SME)" (total assets $\leq$ 35 m€) and "large" (total assets $>$ 35 m€).

In addition to age and size, I also take into account whether a firm experiences high-growth. Specifically, I declare a firm-year observation to be of a high-growth firm if the three-year average for the years prior to the monetary policy shock (periods $t-3$ to $t-1$) for any of gross sales, employment or total fixed assets, is larger than 20%.

[7] Alternatively, one could specify the regression such that one group constitutes the baseline and the other estimates are expressed relative to that. In estimating the regression group-by-group, I follow the main specification by Cloyne et al. (2018). Yet, the authors conclude that the alternative does not yield different results in their application.

4 Results

The first subsection 4.1 presents the findings from the Random Forest. Subsequently, I discuss the dynamic response of investment to an exogenous change in monetary policy for the average firm (4.2) followed by heterogeneity in transmission for different firm groups (4.3). In a last step, results in subsection 4.4 confirm the stability of the key results for different robustness exercises.

4.1 Relevant dimension of heterogeneity

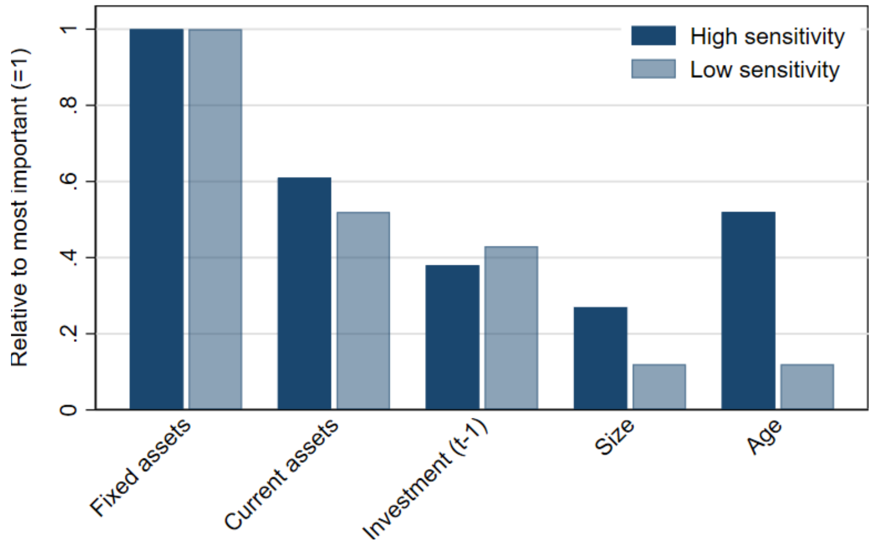
The results of the Random Forest reveal that age and size appear to be more important for explaining investment variability for firms that have a relatively higher elasticity to monetary policy. This finding is derived by comparing the variable importance of potential explanatory variables with respect to investments across the firms that exhibit a high investment elasticity to monetary policy and those with low sensitivity. Firms are split into high and low sensitivity firms based on their investment elasticity to monetary policy estimated by $\hat{\beta}_{i,h}$ from the regression specified in equation (1).[8] In order to take into account that monetary policy may take time to fully transmit to the real economy, the outcome variable considered is the cumulative change in cumulative change in total fixed assets between period $t-1$ and $t+3$, which corresponds to the trough in the dynamic response.

Figure 2 shows the five most important characteristics for these two groups of firms, which happen to coincide (the relative importance for all 25 explanatory variables considered can be found in Figure C.2 in Appendix C).[9] Each of the bars is expressed relative to the most important variable, which is normalized to one, within each of the two groups. The three most important variable, the share of fixed assets and current assets as well as previous investment, are of relatively equal importance for both high and low sensitivity firms. In contrast, age and size appear to play a larger role for explaining investment variability for high sensitivity firms relative to low sensitivity firms. In the next step of the analysis, I build on this insight and estimate impulse responses for different firm groups in order to quantify differences in transmission.

[8] The split is performed along the median across $\hat{\beta}_{i,h}$ estimates. Estimates that are not statistically significant at the 10% significance level are set to zero.

[9] Since the algorithm takes a long time to run for very large data sets, I repeatedly draw a random subsample of 5% of the entire sample and run the Random Forest several times. I can confirm that the variable importance across these draws of firms are highly consistent.

Figure 2. Variable importance of investment.

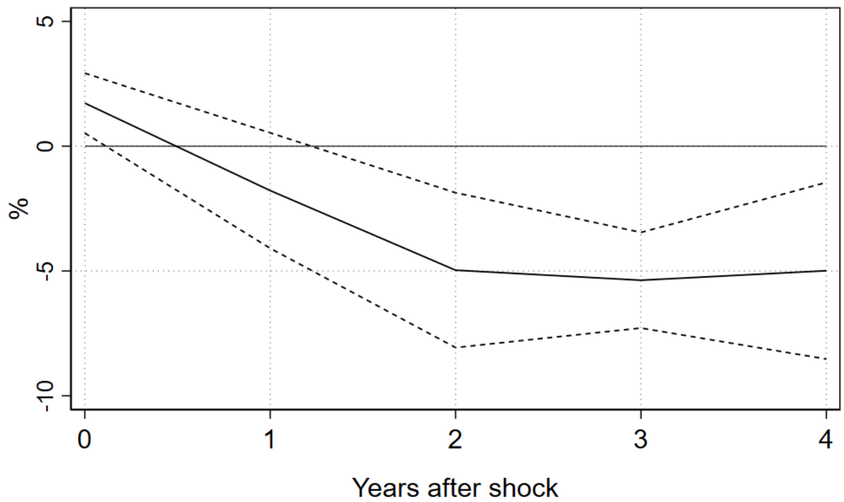


Note: The split of high vs. low sensitivity firms is based on the investment elasticities to monetary policy estimated by $\hat{\beta}_{i,h}$ from the regression of (1). The dependent variable used for the Random Forest algorithm is the cumulative change in total fixed assets between period $t-1$ and $t+3$. All explanatory variables are lagged by one period. Fixed assets and current assets are expressed in percent of total assets. Investments for period $t-1$ are the investment in total fixed assets from period $t-2$ to $t-1$. Size is measured based on total assets.

4.2 Average investment response

Figure 3 shows the IRF to a 25bps monetary policy tightening shock (interest rate increase) for the average firm in the sample. The transmission materializes with a time lag, showing a statistical significant decline after two years and a trough of -5% three years after the shock. The magnitude of the effect appears reasonable both in comparison to aggregate effects as well as micro-level estimates. It is larger than the usual fall in GDP (see, e.g., the collection of estimates in Ramey (2016)), which is to be expected as investments are the most volatile component of GDP. In addition, the reduction is larger than the aggregate fall in investment, which I estimate to be as high as -3%. Again, this is expected since the average firm is rather small and young (as seen in Table 1) and these firms tend to be more sensitive to aggregate fluctuations. Moreover, aggregate investments include investments by the public sector and households as well as investments in intangible capital. In particular public investments are less volatile than those of the corporate sector, which is again in line with the differences in magnitudes in transmission. In comparison to firm-level responses of investments to monetary policy shocks my estimate lies also well in line with previous findings. The magnitude is very close to the average investment responses estimated by Crouzet (2021) and Cloyne et al. (2018), who obtain an average trough effect of investments of -4.8% and -6.5% respectively.

Figure 3. Average investment response.



Note: Figure 3 shows the IRF to a 25bps MP tightening shock from the local projections as specified in equation (2) of the sample average where $\Delta_h Y_{i,t+h}$ is the cumulative change in total fixed assets between period $t-1$ and projection horizon $t+h$. The dashed line is the 90% confidence interval using Driscoll and Kraay (1998) standard errors.

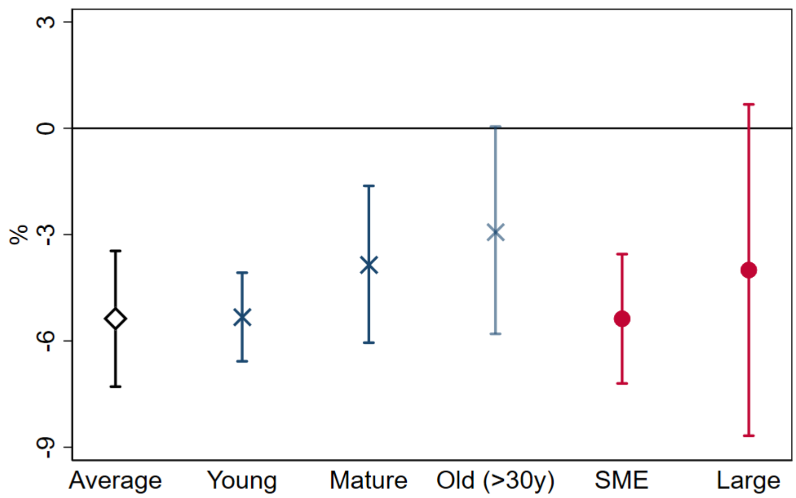
4.3 Heterogeneity in transmission

Firm age and size. The IRFs across firm age and size reveal that the sensitivity of investment to monetary policy declines as age and size increase. The investment response after three years ($h = 3$) across groups is presented in Figure 4. At the left, the average response, corresponding to estimated response after three years in Figure 3, is shown. In addition, the blue lines with a star-shaped marker are the responses for different age groups and the red lines with round markers for size groups respectively.

Both younger and smaller firms respond similarly to the average firm, with a point estimate close to -5%. In contrast, the transmission to older and large firms is smaller and the confidence intervals widen. When looking at an additional subgroup across age, namely firms of age older than 30 years, the point estimate becomes insignificant and equally, the response of large firms is statistically not distinguishable from zero. When comparing the point estimates of young and old as well as SME and large firms, I can further reject the hypothesis that the estimates are the same. Hence, we can conclude from these estimations that investments of younger and smaller firms are more responsive to changes in monetary policy.

These findings are in line with results from the related literature. For example, in the early work on the financial accelerator mechanisms, Gertler and Gilchrist (1994) find that small manufacturing firms are more responsive to changes in interest rates than large manufacturing firms. Similarly, differential transmission along size has been confirmed by Kashyap et al. (1996) in work on the bank lending channel of monetary policy. A more recent paper, that looks at monetary policy transmission across firm age, Cloyne et al. (2018) document that younger firms are more responsive to monetary policy.

Figure 4. Investment response across age and size ($h = 3$).



Note: Figure 4 shows the IRF for the average as well as firm groups as in equations (2) and (3) respectively where $\Delta_h Y_{i,t+h}$ is the cumulative change in total fixed assets between period $t-1$ and projection horizon $t+h$. The projection horizon is $h = 3$, which corresponds to the trough in the dynamic response. The specification of firm groups is $G_{age} \in \{g_1$: young $\leq$ 15 years, g_2: mature $>$ 15 years, g_3: old $>$ 30 years$\}$ and $G_{size} \in \{g_1$: SME $\leq$ 35m€, g_2: large $>$ 35m€$\}$. The error bands are the 90% confidence interval using Driscoll and Kraay (1998) standard errors.

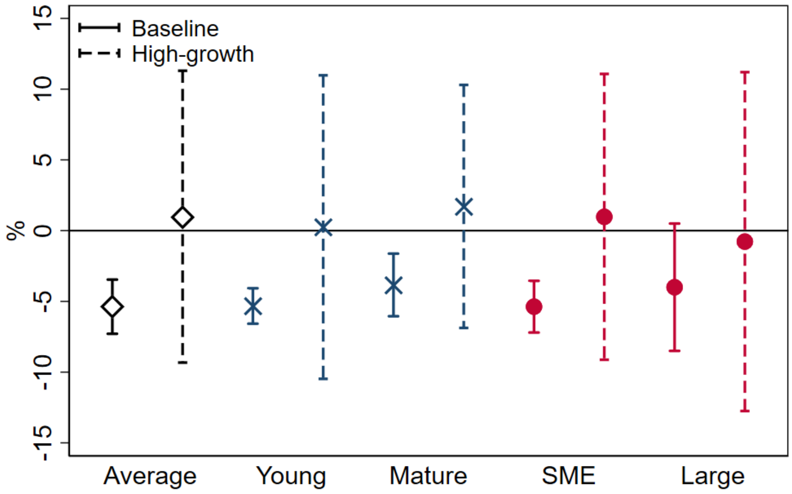
High-growth firms. Based on this finding, it appears interesting to further consider to what extend there may be differences in transmission to firms that are experiencing high-growth. These firms are often young and have not yet reached their optimal scale. At the same time, they are very important for the aggregate economy since they significantly contribute to job creation and spur innovation (e.g., Decker et al. (2014)). Hence, as an additional characteristic, I consider whether a firm experiences high growth or invests a lot, which is defined as average growth in employment, gross sales or fixed assets over three years prior to the monetary policy shock, exceeding 20%. In addition, I look at the combination of high-growth firms with the groups of age and size specified earlier, so to see whether there are any differences in transmission of this subset of firms along the age and size dimension.

The response of this subgroup of firms at the average as well as across age and size groups is shown in the dashed lines of Figure 5. Clearly, these firms are insensitive to changes in rates, both on average as well as across size and age, which is in contrast to the previously discussed findings. The point estimates line up closely on the zero line and the confidence intervals are very wide.[10] Therefore, I conclude that high-growth firms do not respond to changes in monetary policy, regardless of age and size.

The finding that firms which experience high growth are not responsive to monetary policy is in contrast with findings from the previous literature. To the extend that expanding firms are more likely to face binding financial constraints it would be expected that these firms are more responsive to changes in aggregate financial conditions brought about by monetary policy (see, e.g., Barlevy (2003), Davis and Haltiwanger (2019), Dinlersoz et al. (2019)). Interestingly, in his work Huber (2018) finds that a plausibly exogenous lending cut for a large German bank affected in particular firms with high innovation activity, which presumably would be firms experiencing higher growth. Hence, there seems to be a peculiar tension in the findings I present for the subset of high-growth firms vis-à-vis previous work, which appears worth exploring further.

[10] Given the large dataset, these additional group splits lead to a sizeable amount of observations, such that the insignificant results are not due to low statistical power.

Figure 5. Investment response of all firms and subset of high-growth firms across age and size ($h = 3$).



Note: Figure 4 shows the IRF for the average as well as firm groups as in equations (2) and (3) respectively where $\Delta_h Y_{i,t+h}$ is the cumulative change in total fixed assets between period $t-1$ and projection horizon $t+h$. The projection horizon is $h = 3$, which corresponds to the trough in the dynamic response. The specification of firm groups is $G_{HG} \in \{g_1$: three-year average employment growth or sales growth or investing $> 20\%\}$, $G_{age} \in \{g_1$: young ≤ 15 years, g_2: mature > 15 years, g_3: old > 30 years$\}$ and $G_{size} \in \{g_1$: SME ≤ 35m€, g_2: large > 35m€$\}$ as well as the respective combinations of groups. The solid line shows the response of all firms (including additional age and size bins) and the dashed lines are the responses of the subsample of high-growth firms (including additional age and size bins). The error bands are the 90% confidence interval using Driscoll and Kraay (1998) standard errors.

4.4 Robustness

In the following, a series of robustness exercises for the empirical findings is presented. For all these additional estimations, the key results can be confirmed. The results are not shown in the draft but can be obtained upon request.

Changes in the monetary policy environment. In order to test for potential differences in transmission across the sample period, which might affect different firms in different ways, I estimate the regressions *(i)* on different subsample and *(ii)* replace the aggregate control of the short-term interest rate by a shadow rate estimate, which captures interest rate constellations in the absence of a lower bound. For *(i)*, I re-run the estimations using only observations until 2011 and 2016 respectively. The former is the point in time where the ECB first departed from its usual policy tools and started engaging in unconventional monetary policy. Specifically, in December 2011 the ECB decided 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 2016 concerns emerged that the policy rate might have reached the lower bound. While this turned out not to be the case later on, the concern itself might have presented a first constraint in the transmission of policy and can be understood as the first moment where the effective lower bound appeared to hinder policy decisions, from a real-time perspective. For *(ii)*, I use the full set of data but instead replace one of the aggregate controls by a summary measure of alternative shadow rate estimates. Since the individual shadow rate estimates are sensitive to the method by which they have been constructed, I 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). In line with the suggested dating for the conduct of unconventional monetary policy, the standard short-term risk-free rate is extended by the changes in the principal component of the various shadow rates from 2012 onward. For both the sub-sample analysis as well as the estimation using the shadow rate as an aggregate control, I can confirm my results.

Alternative monetary policy shocks. Instead of computing the raw sum of shocks for a year, I test whether a weighted sum of the shocks may alter the results. This alternative way of aggregation has for example been used by Gertler and Karadi (2015). Each of the surprises is weighted by the share of days within the year between the event and the next policy meeting. Through the weighting, the aggregated series pays more consideration to the timing of the shocks during the year. All of the previously outlined findings hold trough, when instead using a time-weighted monetary policy shock series.

5 Discussion of potential mechanisms

The empirical findings suggest several potential hypotheses, which could explain the underlying dynamics, in particular of high-growth firms. First, it might be that there is a reallocation effect of monetary policy, shifting resources from low-productivity to high-productivity, and thus high-growth, firms (see, e.g., the work on reallocation across business cycles by Foster et al. (2016)). The fact that high-growth firms are able to acquire resources of low productivity firms, which might need to scale down operations or exit altogether, could explain why these firms do not show a reduction in investments even if the aggregate financial conditions tighten due to the change in the monetary policy stance. Equally, there might be a reallocation of demand from firms going out of business to firms that experience high-growth, which would bolster business activity, including investment behaviour, of high-growth firms.

Second, investment returns of high-growth firms might be independent of changes in aggregate conditions. In particular, if high-growth firms are able to engage in investments with positive net present value irrespective of changes in monetary policy, this could lead to an overall insensitive investment pattern for these firms.

A third potential explanation could be the presence of earnings-based constraints, which have been documented in work by Lian and Ma (2020) and Drechsel (2021). Since high-growth firms are likely to experience large and positive earnings, they may not be as financially constrained as other firms, insulating their investment decisions from monetary policy. In this case, the existence of such constraints, rather than the usually assumed asset-based constraints, could lead to relevant differences in monetary policy transmission.

In the continuation of this project, I will proceed with further investigations into these different mechanisms and building on that, develop a model of heterogeneous firms and monetary policy transmission, where these mechanisms are taken into consideration.

6 Conclusion and next steps

In this paper, I have studied how monetary policy transmission differs across various characteristics of firm heterogeneity. Using a large firm-level data set of euro area firms together with a Random Forest algorithm, I find that both age and size matter for heterogeneity in transmission across firms. For younger and smaller firms, there is a clear reduction in investments in response to monetary policy tightening and the investment decline becomes weaker as age and size increase. In contrast, investments of high-growth firms are not sensitive to monetary policy, for any age and size. I discussed different mechanisms that could explain the insensitivity of high-growth firms, namely a reallocation driven by monetary policy where resources move to high-growth firms. Second, it could be that high-growth firms face different investment returns and that these do not change much when aggregate financial conditions are shifted by monetary policy. Alternatively, this might be suggestive of earnings-based constraints, which are not binding for firms of high-growth.

To further investigate these potential underlying mechanisms, I will inspect the high-growth firms more closely to see which observable characteristics may explain their lack of responsiveness to monetary policy. In addition, it might be helpful to consider a broader set of dependent variables to get a better understanding of potential channels. After this, I will proceed with estimations of the aggregate effects based on the heterogeneous firm group responses identified. Building on the empirical findings, I then plan to build a model of heterogeneous firms, which would help to shed further light into the underlying mechanisms and channels.

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Appendices

A Data details

A.1 Variables and transformation

Firm-level variables:

- Investment: cumulative percentage change in total fixed assets over $h-$periods [TFAS]
- Firm age: computed from the difference of the date of incorporation and the year of reporting
- Firm size: total assets [TOAS]
- Control variables: growth of gross sales [OPRE], share of current assets in total assets [CURAS, TOAS], firm size as log of total assets [TOAS]
- Other: number of employees [EMPL]

All firm-level data series are from the Orbis database. The Orbis identifier is given in square brackets. All firm-level variables have been deflated with the GDP deflator for the respective country, where the base year is 2015. In addition, they are winsorized at the 1% and the 99% level.

Monetary policy shock:

- Baseline: High-frequency surprises in the 3-month OIS rate as provided in the EA-MPD by Altavilla et al. (2019); full event window; only surprises where high-frequency change in stock price moves in opposite direction as change in short-term rate; aggregated to annual frequency.
- Robustness: as above, however, aggregation to the annual frequency as a time-weighted average, taking into account the dating of the event through weighting the surprises by the fraction of days in the year it prevails.

Aggregate variables:

- Short-term risk-free rate: 3-month OIS rate; average over the year.
- Real GDP growth (country level and euro area): enters in log-levels
- GDP deflator (country level and euro area): year-on-year change except for deflating where index is used; base year 2015

The aggregate data series are retrieved from the ECB Statistical Data Warehouse (SDW).

A.2 Coverage and representativeness

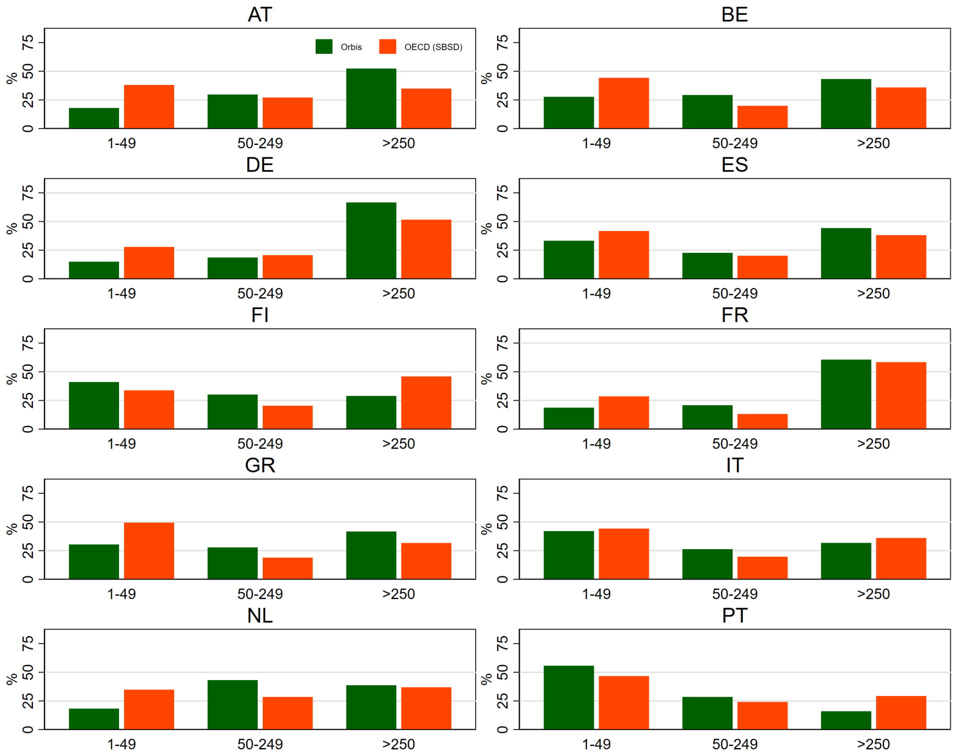
To evaluate the coverage and representativeness of the Orbis data sample, I follow the exercise of Kalemli-Özcan et al. (2019) (Table 1 Coverage and Table 2 Representativeness), which is reported for "Gross output" (see also Appendix C of the authors on the exact details). As reference for the aggregate economy, I use data from the OECD Structural Business Statistics Database (SBSD), which is available at different sectors and across firm size classes (by employment) from 2005 onward. I use the most aggregate sectoral composition referred to as "Business economy, except financial and insurance", which is composed of 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.1: Coverage of the aggregate 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 Orbis variable 'Operating revenue (OPRE)' vs. OECD SBSD variable 'Turnover' by country. Missing entries and time limitations are due to missing entries in the SBSD data.

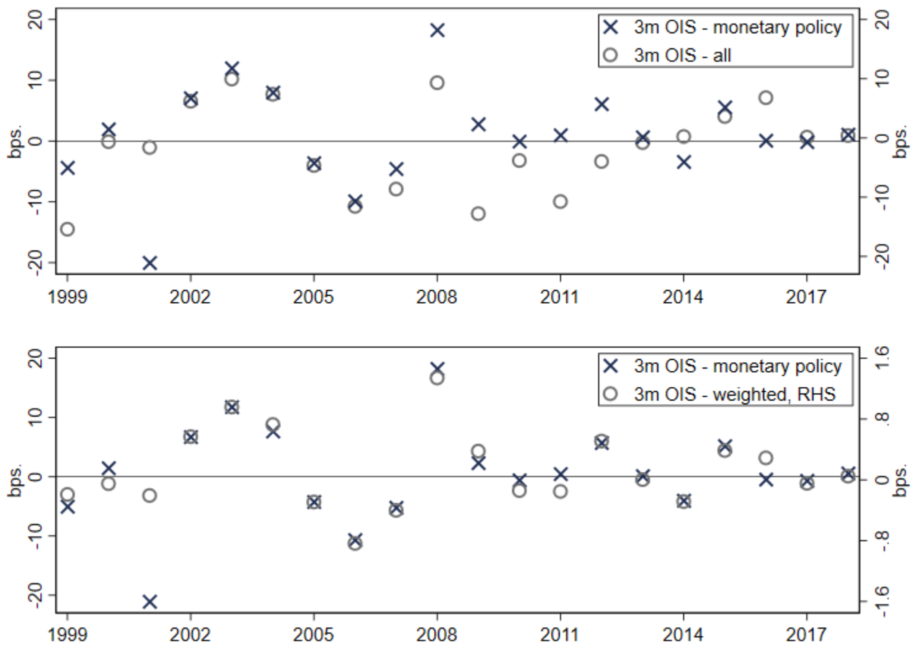
Figure A.1. Representativeness of the size distribution of the firm-level data based on gross output.



Note: Comparison along Orbis variable 'Operating revenue (OPRE)' vs. OECD SBSD variable 'Turnover' by country for the year 2017. The x-axis shows buckets of firm size by number of employees. The green bar is the fraction of firms in a size bin from the Orbis data and the orange bar for the SBSD data respectively. The Orbis data sample is limited to firms where information on the number of employees is available.

B High-frequency surprises

Figure B.1. Time series of shocks.



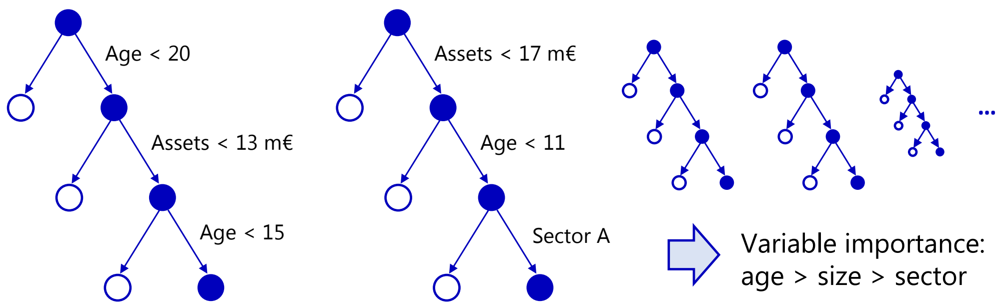
Note: All shocks except '3m OIS - all' have been identified through the cross-asset correlation of the surprises in the respective interest rate and the stock price. The series with the x-marker represents the shock from the baseline estimation.

C Random Forest details

C.1 Illustrative example of the algorithm

This subsection discusses a stylized example of the Random Forest algorithm, where the dependent variable is 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 walk over the subsample and asses multiple times at which sample split along X_i the variation in Y_i is maximized. For continuous variables, the threshold for the sample split is endogenously determined. Subsequently, the procedure is continued along the respective sample splits, following the logic of a decision tree, until an end point is reached (the depth of the tree is a pre-specified input). Figure C.1 presents a hypothetical sketch of this procedure. In accordance with the name of the algorithm, multiple of these trees are created, each on a separate random subsample draw. Across all these 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.

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



C.2 List of potential explanatory variables

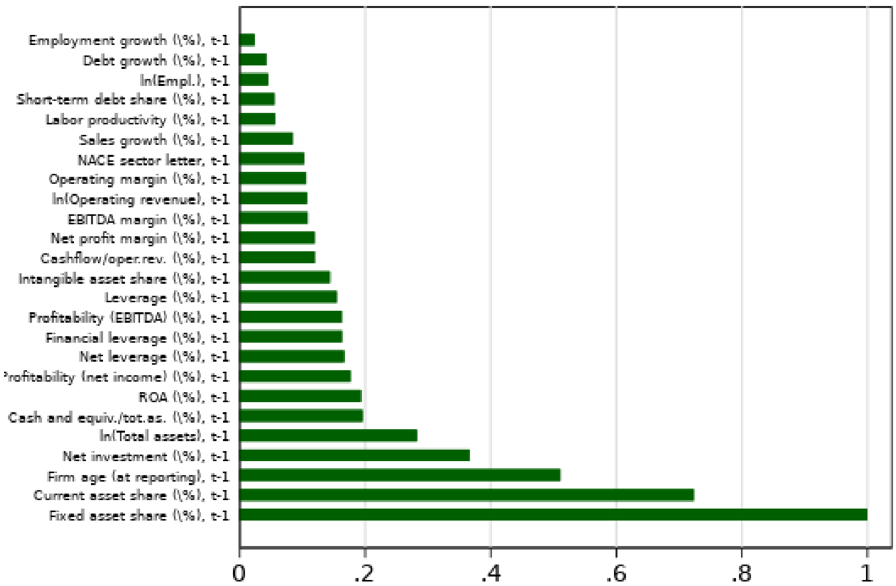
The following list specifies the set of explanatory variables that are given as an input to the Random Forest algorithm described in subsection 3.2. All variables are lagged by one period and expressed in real terms where applicable.

- General characteristics: age, size (total assets, gross sales, employees), sector
- Capital structure: cash and equiv./total assets, cashflow/gross sales, fixed asset share, current asset share, intangible asset share
- Debt structure and debt growth: leverage (total liabilities/total assets), net leverage, financial debt/total assets, short-term debt share, debt growth
- Profitability and margins: net income/total assets, net income/gross sales, EBIT/gross sales, EBITDA/gross sales, gross sales/employees
- Growth $(t-1)$: employment, gross sales, net investment

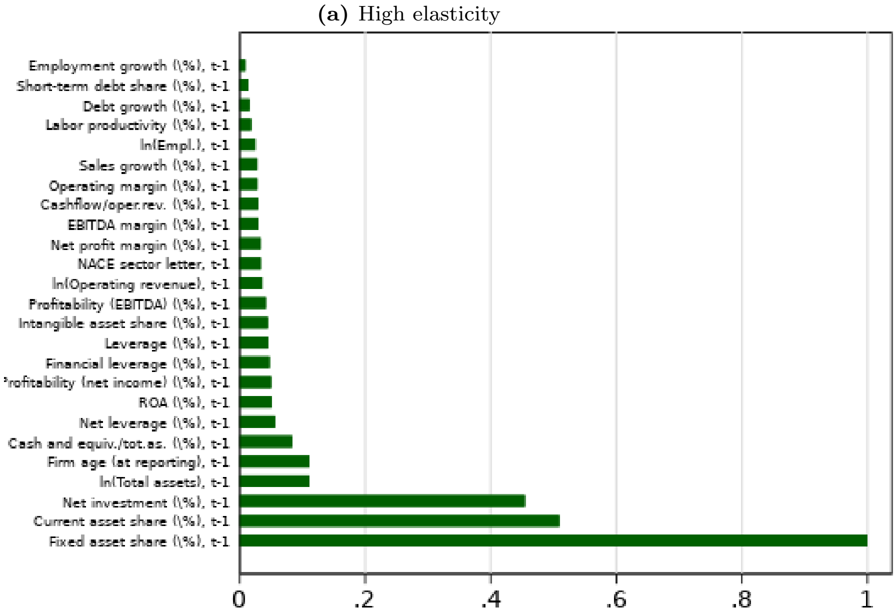
C.3 Variable importance for all explanatory variables

Figure C.2 presents the variable importance for the entire set of explanatory variables of cumulative investments at $h = 3$ for the low and high elasticity firms.

Figure C.2. Variable importance of investment (all variables).



(a) High elasticity



(b) Low elasticity

Note: The split of high vs. low sensitivity firms is based on the investment elasticities to monetary policy estimated by $\hat{\beta}_{i,h}$ from the regression of (1). The dependent variable used for the Random Forest algorithm is the cumulative change in total fixed assets between period $t-1$ and $t+3$. All explanatory variables are lagged by one period.