Corporate leverage and the effects of monetary policy on investment: A reconciliation of micro and macro elasticities*

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Abstract

We investigate how the level of corporate leverage affects firms' investment response to monetary policy shocks. Based on novel aggregate time series estimates, leverage acts amplifying, whereas in the cross section of firms, higher leverage predicts a muted response to monetary policy. We use a heterogeneous firm model to show that in general equilibrium, both empirical findings can be true at the same time: When the average firm has lower leverage and therefore reduces its investment demand more strongly after a contractionary shock, the price of capital declines sharply, which incentivizes all firms regardless of their leverage to invest relatively more, muting the aggregate decline of investment. We provide empirical evidence supporting this hypothesis. Overall, if there are general equilibrium adjustments to shocks, effects estimated by exploiting cross-sectional heterogeneity in micro data can differ substantially from the macroeconomic elasticities, in our example even in terms of their sign.

JEL classification: D22, E32, E44, E52

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1 Introduction

Is the investment response to monetary policy shocks stronger or weaker when leverage in the corporate sector is high? From a policy perspective, this question is important because of the large dispersion of leverage across firms and time. If firms' responsiveness to monetary policy varies with leverage, this may change both the magnitude of the aggregate investment response to monetary policy and its distributional effects on different firms. We study this question at two different levels, namely, at the aggregate ("macro") level and at the firm ("micro") level and find widely different results. We then offer a general equilibrium explanation that reconciles the difference between micro and macro elasticities. Our explanation is supported by a New Keynesian model with financial frictions, which we use to study the role of leverage in the transmission of monetary policy across heterogeneous firms and across time.

Our first empirical result is that leverage in the corporate sector amplifies the effects of monetary policy shocks on firms' investment and, by extension, the capital stock. We provide novel evidence of this fact by estimating several nonlinear time series models on aggregate US data. When aggregate leverage in the corporate sector is one standard deviation above its historical mean, i.e., when the average firm is highly indebted, investment contracts twice as much as under average leverage levels.

This first contribution stands, at least at first sight, in sharp contrast to the elasticities estimated by Ottonello and Winberry (2020), who use firm-level micro data to show that the investment response of firms with high leverage is less negative than that of firms with low leverage. The second contribution of our paper is to replicate and confirm their result with data from a different source, extending the dataset in terms of both time (by the 12 years of the period after the global financial crisis) and geography (by including euro area firms). Both the micro and macro elasticity estimates are robust to various definitions of leverage, samples and specifications.

The third contribution is that we provide an explanation for what seem to be contrasting estimates from micro data and aggregate time series. In general equilibrium, each firm's investment decision is affected by the price of capital, which is a function of investment demand by all firms in the economy. While the (partial equilibrium) micro elasticity describes the difference between high- and low-leverage firms at a given point in time, in the aggregate, the distribution of leverage among all firms matters, too. We calibrate different versions of the Ottonello and Winberry (2020) New Keynesian model with heterogeneous firms and financial frictions, which generate a convex marginal cost of investment curve that mutes the response to interest rate changes for high-leverage firms. We show that even within that modelling framework, in a counterfactual economy where the average firm has higher leverage, aggregate investment responds more strongly to monetary policy even though high-leverage firms are less responsive, echoing our empirical results.

Our central insight is the following: If monetary policy tightens and the partial equilibrium demand for investment falls, the relative price of capital decreases, which *ceteris paribus* dampens the decrease in investment. When most firms are highly leveraged and – as our firm-level results confirm – react little to monetary policy, the decrease in the relative price of capital after a contractionary monetary policy shock is small. Because the relative price of capital stays relatively high, *all* firms, regardless of their leverage level, are discouraged to invest, leading to strong aggregate effects. If, in contrast, many firms have low leverage and reduce investment demand strongly after a contractionary shock, the substantially lower price of capital incentivizes all other firms to invest more, relative to the case where most firms have high leverage. Therefore, the aggregate effects of tighter monetary policy on investment are less negative in times of low leverage. We provide empirical support for our hypothesis. Most importantly, we find time series evidence that in a high-leverage economy, the relative price of capital increases after a contractionary monetary policy shock, relative to a low-leverage economy.

We consider several alternative hypotheses that could potentially reconcile the diametrically opposing micro and macro elasticities but find no support for them in the data. In particular, we consider the fat-tailed size distribution in the firm data, in which a few large firms are responsible for a large share of aggregate fluctuations (Gabaix, 2011, Crouzet and Mehrotra, 2020). Therefore, in the aggregate, the cumulated investment by a few large firms could override disinvestment of a large mass of small firms or vice versa. We find no evidence that the skewness of the firm size distribution explains the difference between firm-level and aggregate results. Another explanation might be the selection of firms in our sample, both unconditionally – because we observe a particular set of firms with potentially different characteristics than the average firm – or conditional on the monetary policy shock, after which some firms endogenously drop out of the firm sample, whereas their capital lives on in the aggregate statistics. While these hypotheses can be a source of bias between micro- and macro-based elasticities, they cannot explain the opposing signs of our estimates.

Methodologically, we use aggregate-level time series data and firm-level balance sheet data to estimate nonlinear local projections. The coefficient of interest that we aim to identify is an interaction term between the predetermined level of leverage – various types of debt relative to assets – and exogenous changes in interest rates. To identify monetary policy shocks, we follow Jarociński and Karadi (2020) and use high-frequency changes in interest rates around central bank announcements, taking into account the potential information effects of these announcements.

Related literature. The literature has long highlighted that leverage can amplify the effects of shocks on real outcomes (Kiyotaki and Moore, 1997, Bernanke et al., 1999, Giroud and Mueller, 2017). Nevertheless, even though a model with a financial accelerator produces larger aggregate responses to shocks than a model without macro-financial linkages does, higher leverage can still be associated with lower responsiveness in the former model, as is, for example, the case in Ottonello and Winberry (2020). Goodhart et al. (2022) argue that monetary policy has larger effects on output (and smaller effects on inflation) when corporate leverage is elevated because debt service payments act as a cost channel. We provide novel evidence that corporate leverage has indeed strongly amplifying effects on aggregate real outcomes. To the best of our knowledge, the only other paper that has studied how corporate leverage changes the effects of monetary policy at the aggregate level is Auer et al. (2021), which uses euro area time series at the sectoral level and investigates the response of industrial production.[1] While our data and empirical setup differ, their result that manufacturing output tends to be more sensitive to monetary policy when the average firm has higher leverage is consistent with our findings.

We contribute to the literature on the time-varying effects of shocks in general and monetary policy in particular. For example, several papers have argued that monetary policy is less effective in influencing the real economy during economic downturns (e.g. Tenreyro and Thwaites (2016), Alpanda et al. (2021), although this has recently been questioned by Bruns and Piffer (forthcoming)). Corporate leverage is moderately countercyclical. Therefore, based on our time series estimates showing that high leverage leads to more negative investment responses, we would expect the general business cycle dependence of the monetary policy effects to be driven by factors other than corporate leverage. For policy-makers, time-variation in the effectiveness of monetary policy is highly relevant, and we investigate a quantitatively important source of such time variation. The literature has highlighted many other dimensions of state dependence (e.g. Iwata and Wu (2006), Castelnuovo and Pellegrino (2018), Ascari and Haber (2022) or Eichenbaum et al. (2022)).

Our second contribution – the replication of Ottonello and Winberry (2020)'s result that high-leverage firms' investment falls less after a contractionary monetary policy shock – is aligned with recent literature on the heterogeneity in balance sheets in the transmission of monetary policy. Some studies that have addressed the same question have argued that leverage amplifies the responsiveness of firms' real quantities, such as investment and employment, to shocks or that there are no statistically significant differences between high- and low-leverage firms (see, for example, Durante et al. (2022), in the case of public and privately owned European firms, Bahaj et al. (2022) in the case of the UK and Cao et al. (2023) in the case of Norway). To the best of our knowledge, all these studies differ from our specification in that they use both the within- and across-firm variation of leverage simultaneously or across-firm variation only (in the case of Caglio et al. (2022)). In contrast, we follow Ottonello and Winberry (2020) and use only within-firm variation to identify the coefficient of the interaction term of leverage and monetary policy shocks. This accounts for a substantial role of permanent (and unobserved) firm-level differences in shock responsiveness. Using an alternative identification strategy, Vats (2023) also finds that leverage mutes the firm-level response to monetary policy.

A large body of previous work highlights dimensions of heterogeneity in firms' responsiveness to monetary policy. For example, investment of young and small firms tends to be more sensitive to monetary policy (Gertler and Gilchrist, 1994, Cloyne et al., 2023, Gnewuch and Zhang, 2022). Age and size could be confounding factors that affect our results because they are both correlated with leverage. However, our results do not seem to be driven by that correlation. For example, we show that the result is qualitatively and even quantitatively similar across firm

[1] Holm-Hadulla and Thürwächter (2023) jointly study leverage shocks and monetary policy shocks in the euro area.

size bins, although we estimate effects for the smaller firms with less precision.

Several recent papers show that in addition to leverage, there are other important determinants of the propagation of monetary policy related to corporate balance sheets, for example, the maturity of debt (Jungherr et al., 2022), whether the debt is market-based or granted by banks (Alder et al., 2023), or the size of liquidity holdings (Jeenas, 2024). The price of outstanding debt is another determining factor. According to Ferreira et al. (2023), firms with a high excess bond premium (EBP) – a high credit spread relative to the objective default risk – respond less to monetary policy shocks in terms of their investment, but their credit spreads are more responsive. The EBP is by construction orthogonal to a firm's leverage, which is our main heterogeneity dimension of interest. Nevertheless, Anderson and Cesa-Bianchi (2024) also find that the EBP plays a role in the way leverage affects the transmission mechanism of monetary policy to the corporate sector: In high-leverage firms, funding costs and particularly the EBP are more sensitive to monetary policy.[2]

Ultimately, our results support theories with heterogeneous firms in which this heterogeneity impacts aggregate outcomes, but also highlight that what is true for heterogeneity in the cross-section does not automatically translate to heterogeneity across time. This logic extends well beyond monetary policy or business cycles. The wider availability of more granular datasets has made it possible to identify macroeconomic relationships from cross-sectional heterogeneity across firms, households or locations in ways that require much less restrictive identifying assumptions than often required to obtain time series estimates. However, micro-econometric estimates can differ substantially from macro-based estimates. They can be smaller, as has been documented extensively in the labor supply literature (Rogerson and Wallenius, 2009, Chetty et al., 2011) or in more recent papers on the slope of the Phillips curve (Hazell et al., 2022). Micro-econometric estimates can also be larger, as has recently shown to be the case with respect to marginal propensities to consume (Orchard et al., 2023). Differences between micro and macro elasticities are often attributed to either general equilibrium, which in many panel data estimations are absorbed by time fixed effects, or aggregation in combination with heterogeneous effects or an extensive margin.[3] In our case, elasticities estimated at the micro and macro levels differ not only in terms of magnitudes, but also in their sign, and we argue that the price feedback in general equilibrium is responsible for this. These potential adjustments should be considered carefully when deriving aggregate implications from estimates based on cross-sectional heterogeneity.

[2]Unlike these authors, we do not observe firm-level credit spreads in our firm-level data. In the aggregate, however, we find that corporate bond spreads react more to monetary policy shocks when leverage is high and that this state dependence is also – but not only – driven by the excess bond premium.

[3]Koby and Wolf (2020) discuss aggregation and equilibrium in the context of heterogeneous firm models as well, but the meaning differs. They study the role of the lumpiness of firm-level investment decision for aggregate responses. If investment demand is very price-sensitive, such as in Khan and Thomas (2008), the general equilibrium price response smooths out the state dependence of firm-level responses, and the cross-sectional distribution of firms becomes irrelevant. If the price elasticity of investment demand is lower, as in Winberry (2021), the asymmetry introduced by lumpy investments survives in general equilibrium. As a result, monetary policy is less effective in recessions.

Our paper is organized as follows. Section 2 provides time series evidence of the macro elasticity. In Section 3, we estimate the micro elasticity using firm-level balance sheet data. Section 4 performs various robustness tests of both the macro and micro elasticities and consistently finds estimates of the opposite sign. In Section 5, we show that spillovers via the equilibrium price of capital can explain both pieces of empirical evidence jointly. Section 6 discusses several alternative hypotheses. Section 7 concludes.

2 Evidence from aggregate time series

In this section, we document the state dependence of monetary policy in the aggregate using time series data. We find that the effect on aggregate investment is significantly stronger (more negative) in times of high corporate leverage.

2.1 Methodology

We estimate local projections of the following form:

$$I_{t+h} - I_{t-1} = c_h + \alpha_h \, \Delta R_t + \beta_h^{\text{macro}} \, L_{t-1} \, \Delta R_t + \mathbf{\Gamma'}_h \mathbf{Z}_{t-1} + e_t, \tag{1}$$

where I_t is the log of real investment in quarter t, c_h is a horizon h-specific constant, ΔR_t is the change in the federal funds rate between the end of quarter $t-1$ and t, and L_t is a measure of the state of aggregate leverage in the corporate sector. The main coefficient of interest is $\hat{\beta}_h^{\text{macro}}$, which estimates the differential response of investment to monetary policy when predetermined leverage is high for each horizon h between 0 and 16. The vector $\mathbf{Z}$ contains 4 lags of time series covariates to control for endogenous changes in the short-term policy rate to inflation and the business cycle. We include in these covariates the sequential growth rates of GDP and investment, inflation as measured by the CPI, core CPI, PPI, and the investment deflator,[4] the level of corporate bond yields relative to a risk-free asset with the same maturity (compiled and provided by Gilchrist and Zakrajšek (2012)), lags of leverage and previous changes in the federal funds rate itself.[5]

To isolate exogenous changes in ΔR_t, we use the high-frequency, information-effect adjusted

[4] As we will discuss in Section 5, the relative price of capital is an important aspect of the state-dependent transmission of monetary policy and should therefore be included in the control variables. Our control variables account for this by including the investment deflator as well as different measures of output prices. All our results are robust to using the relative price of investment goods by DiCecio (2009) instead.

[5] The right-hand side of Equation (1) closely resembles a reduced-form VAR in growth rates. Since cumulated growth rates enter on the left-hand side, the vectors of estimators $\hat{\alpha}_h$ and $\hat{\beta}_h^{\text{macro}}$ can be interpreted as impulse response functions of the level of investment. Our choice of local projections allows, first and foremost, a highly flexible inclusion of the interaction term $L_{t-1}\Delta R_t$. Additionally, the vector of variables $\mathbf{Z}_{t-1}$, which help to identify orthogonal changes in R_t, can more easily be extended without an exponentially growing number of parameters. The downside of our local projection estimation is that it can come at the cost of a higher variance than estimations produced by a VAR (Li et al., 2022). In this sense, our confidence intervals can be considered a conservative upper bound. We present estimates from a nonlinear VAR as a robustness check.

announcement surprises ξ_t^m as an instrument for changes in the federal funds rate.[6] We use the surprises provided by Jarociński and Karadi (2020), though we will establish robustness with respect to other shock measures as well. We prefer the implementation in an IV setting, as opposed to reduced-form estimates, for two reasons. First, inference on the reduced-form version is complicated by the fact that the variance in the high-frequency shocks is very small, leading to large standard errors in time series applications with relatively small samples like ours. Therefore, it is more desirable to implement a 2SLS estimator, which is independent of the variance of ξ_t^m other than through its explanatory power for ΔR_t, which is very strong. The F-statistic on the first stage regression is 27.2, well above commonly used critical values for weak identification. The second reason is that the 2SLS estimate conveniently scales all elasticities to a 1pp short-term interest rate shock.

2.2 Data

We measure I_t as real gross private domestic investment from the US national accounts. Table A1 in the appendix lists the details and sources of all the time series used, including control variables.

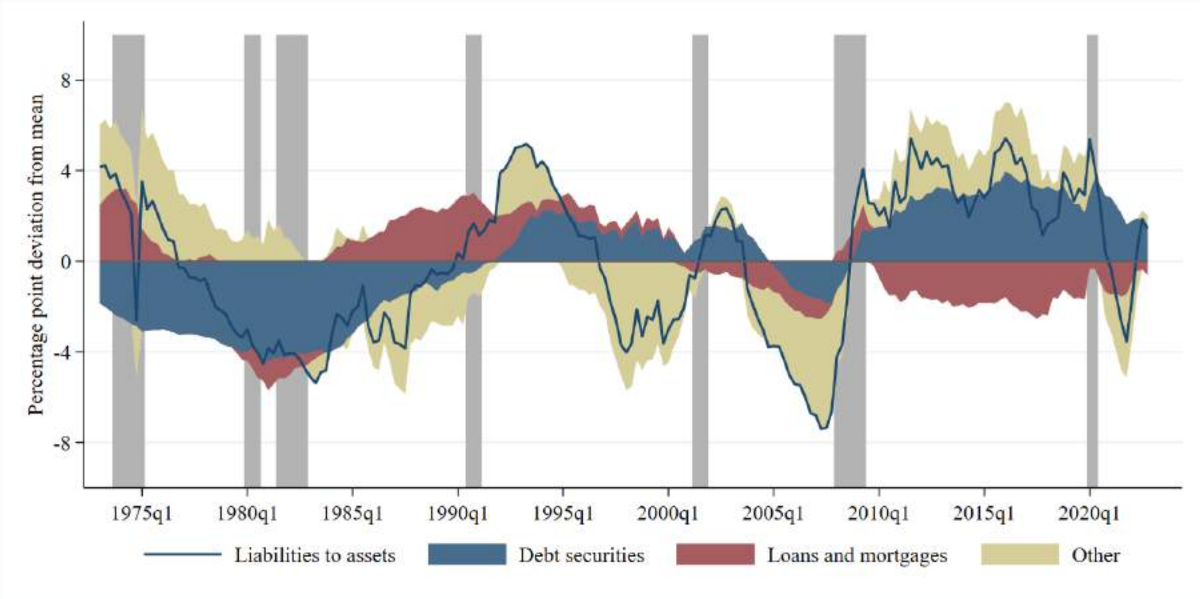
To measure the state of corporate leverage L_{t-1}, the baseline specification uses the ratio between the sum of all liabilities and all assets held by the entire nonfinancial business sector from the financial accounts. This measure is depicted as the solid line in Figure 1 in deviations from its historical mean of 46%. Historically, this measure has fluctuated between 40 and 52%, with a standard deviation of 3pp. Aggregate leverage is weakly countercyclical: The correlation coefficient with the output gap (CBO definition) is -0.23. This is despite the fact that firms repurchase debt and reduce equity payouts in recessions.[7] However, there are notable exceptions to the general countercyclicality. For example, corporate leverage was low and decreased further during the recessions of the early 1980s. In the late 2010s, corporate leverage stayed elevated even as the economy recovered from the Great Recession.

The colored areas in Figure 1 show the sources of fluctuations in leverage from the three types of liabilities reported in the financial accounts: i.) Market-based debt securities, ii.) loans and mortgages from banks and iii.) miscellaneous sources of credit such as suppliers, lease and pension obligations, deferred taxes or unclassified liabilities. Their historical averages in terms of percent of total corporate assets are 12, 10 and 25%, respectively. Figure 1 shows that the comovement of the three liability types is imperfect, reflecting the fact that the corporate

[6] High-frequency surprises measure the change in interest rates (the three-months Federal Funds futures in the case of the US) around narrow windows of monetary policy announcements. As financial markets incorporate all available information prior to these announcements, these surprises ought to be orthogonal to all other shocks affecting the economy and its firms (Gertler and Karadi, 2015). Jarociński and Karadi (2020) argue that these shocks can contain information both on unexpected innovations to the monetary policy stance, as well as on the central bank's assessment of the economy, which it communicates to the market through interest rate changes. They isolate the true change in the monetary policy stance from these surprises using sign restrictions on asset price responses. We take the quarterly sum over all announcements in a quarter.

[7] See Covas and Den Haan (2011) and Jermann and Quadrini (2012) for a discussion of the cyclicality of corporate debt and equity.

Figure 1: Corporate leverage over time



Notes: The solid line shows our baseline measure of aggregate corporate leverage, computed as the ratio of end-of-period market values of liabilities to assets in the nonfinancial corporate business sector from the US financial accounts, whereas we subtract the historical mean of 46%. The colored areas show how different sources of external funds (capital markets, banks and others such as suppliers) contribute to time variation in leverage. NBER recessions are shaded in gray.

funding structure can vary over the business cycle (Crouzet, 2018, Lhuissier and Szczerbowicz, 2022). For example, in the period after the Great Recession, corporate leverage from debt securities reached an all-time high in the US, whereas bank loans and mortgages were scarce.

We prefer to define leverage broadly, i.e., inclusive of liabilities regardless of the funding source, because the default risk of a company depends on all financial obligations, not simply (market- or bank-funded) debt in a narrower sense. The fact that over half of liabilities are classified as "miscellaneous" in the financial accounts shows that firms classify liabilities in ways that are difficult to harmonize; thus summing over all possible liabilities is the most consistent way to do so. Nevertheless, we will show in Section 4 that our main result is robust to measuring leverage in terms of debt (defined as the sum of debt securities and loans and mortgages) only, despite the limited correlation of the two.

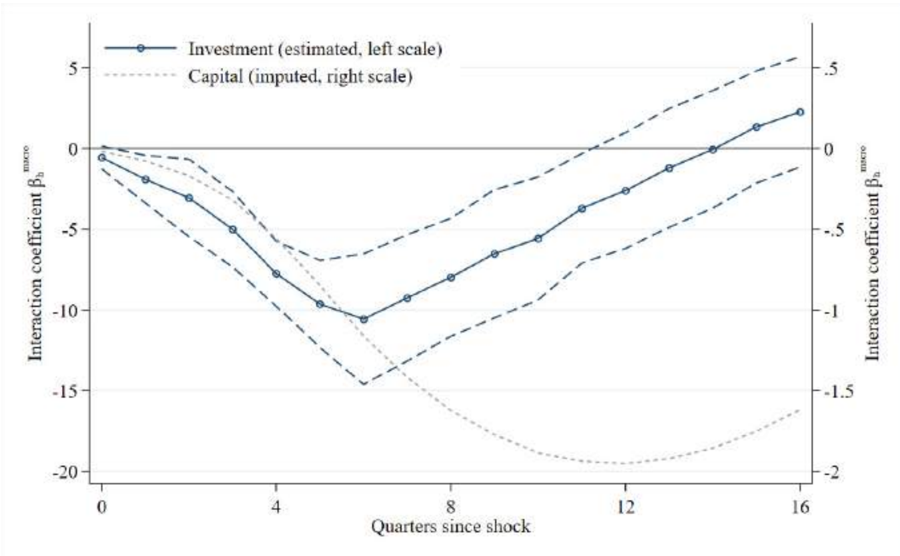
Unless mentioned otherwise, we use a standardized version of L_{t-1} such that $\hat{\beta}_h^{\text{macro}}$ can be interpreted as the *additional* effect of monetary policy on investment for every standard deviation of leverage above the mean. The mean and standard deviation of our baseline measure are 46% and 3pp, respectively. Due to the series of monetary policy shocks, the estimation sample for the baseline result is restricted to between 1990q1 and 2019q2.

2.3 Result

The blue lines in Figure 2 show that in times of higher-than-average leverage, the response of investment to a monetary policy tightening is significantly more negative. The bullets show the estimated horizon-specific parameters for the interaction term $L_{t-1}\,\Delta R_t$, and the dashed lines represent the 95% confidence intervals. Already one quarter after the shock, investment decreases statistically significantly more when leverage in the corporate sector is high. The trough effect is reached 6 quarters after the shock. At this point, our model predicts the effect of a 1pp increase in the monetary policy rate on investment to be 10pp larger for each standard deviation that aggregate leverage is above its historical mean.

The negative medium-run differential effects are quantitatively meaningful. In Figure B1 in the appendix, we show the semielasticity of investment to interest rate changes for different absolute levels of leverage implied by the baseline model for the trough horizon $h = 6$, i.e., the derivative of Equation (1) with respect to ΔR_t. At the 95th percentile of historical values of leverage (approximately 52%), the effects of monetary policy on investment are approximately 15pp larger and thus twice as strong than at the mean. If leverage is countercyclical, our results suggest that the effectiveness of monetary policy through the investment channel is higher during periods of economic slack.

Figure 2: Difference of macro elasticity between times of high and low aggregate leverage



Notes: Estimation results of local projections on US time series data (see Equation (1)). The coefficients $\hat{\beta}_h^{\text{macro}}$ for the interaction of a standardized measure of corporate leverage with the (contractionary) monetary policy shock are shown. The historical standard deviation of leverage is 3pp, and the sample period is 1990q1-2019q2. The 95% confidence intervals based on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are shown as dashed lines. The gray dotted line shows the differential response of capital imputed from the investment response and the law of motion of capital (starting from a quarterly reinvestment rate of 3%).

While the outcome variable in our time series analysis is aggregate investment, i.e., purchases of capital, we must rely on estimates of capital stock responses in our micro estimates later on in the paper. To nevertheless compare magnitudes across our macro and micro data estimates, we impute the response of capital using its law of motion.[8] The dotted gray line in Figure 2 shows that capital decreases by approximately 1.5pp more after a monetary contraction if corporate leverage is one standard deviation higher than usual. In our analysis of other outcome variables in the following subsection, we show results for another measure of real corporate capital. These results are consistent with this simple back-of-the-envelope calculation, both qualitatively and quantitatively.

2.4 Other outcomes

In addition to investment, we estimate the differential response of several other outcomes for the US economy by replacing the dependent variable in Equation (1) with alternative macroeconomic aggregates. When estimating the response of variables not yet included in the vector of controls, we add four lags thereof. The impulse response functions are plotted in Figure B3 in the appendix.

The three components of non-residential investment – real investment in structures (which carries a weight of 17% of overall investment over the relevant sample), equipment (35%) and intellectual property products (22%) – all decline more in response to tightening monetary policy when corporate leverage is high.[9] Furthermore, we show that even the response of real corporate capital is significantly stronger in times of high leverage, even though this outcome can be measured only imperfectly.[10]

Aggregate GDP and the unemployment rate are more responsive to monetary policy, too, when corporate leverage is high (see Panels (c) and (d) of Figure B3). Finally, we show the differential response of aggregate financial variables. The federal funds rate itself is somewhat lower in the medium run, as would be expected given the more contractionary response of the real economy. This excludes the possibility that the investment response to a monetary policy shock is stronger in a high-leverage economy because the tightening itself is more persistent. Long-term government yields, in turn, behave very similarly across states. Beyond risk-free rates, we show how corporate bond spreads (by Gilchrist and Zakrajšek (2012)) respond in a high- vs. low-leverage economy. The estimated interaction terms are positive and driven largely by the excess bond premium – i.e., the share of credit cost not attributed to objective default risks. Our findings are in line with the view that credit conditions tighten in response to monetary policy (Gertler and Karadi, 2015), particularly when debt burdens are high. This result is the

[8] Capital evolves according to $K_t = (1-\delta)K_{t-1} + I_t$. In the data, nominal investment in the national accounts has historically been equal to 3% of nominal nonfinancial assets in the financial accounts, on average. We assume that after a monetary policy shock, this investment rate evolves according to the blue estimates in Figure 2 – for example, it decreases by 0.3pp (10% of 3%) in the sixth quarter – and that the depreciation rate remains constant. We iterate through all horizons to compute a counterfactual path for capital.

[9] The two remaining components of investment are residential investment (24%) and changes in private inventories. See Table A2 for the definition of real investment components.

[10] We use the stock of capital at historical cost, which is not exactly equivalent to the nominal stock of capital deflated using the current price of capital but is available in the official statistics of the Federal Reserve Board. The 95% confidence intervals show that the differential response is statistically significant and fully encloses the imputed path of real capital from our back-of-the-envelope calculation in Figure 2.

direct aggregate counterpart to what Anderson and Cesa-Bianchi (2024) show to be the case at the firm level.

Before conducting a range of robustness tests for a negative $\hat{\beta}_h^{\text{macro}}$, which we perform in Section 4, we contrast our findings to the semielasticity of investment by levels of leverage based on firm-level data.

3 Evidence from firm balance sheets

Our macro result that investment is more responsive to monetary policy when corporate leverage is high is – at first sight – at odds with what the literature has shown using firm-level balance sheet data. Most prominently, Ottonello and Winberry (2020) [henceforth OW20] find that the semielasticity of investment to monetary policy depends *positively* on leverage; i.e., that investment falls less when firms have high leverage. To directly compare our estimates to theirs, this section replicates and confirms their result. In doing so, we extend the sample of balance sheets to include euro area firms as well as the period after the Great Recession, which we see as a contribution of this paper.

3.1 Methodology

Like OW20, we estimate the differential dynamics of investment for different levels of leverage with local projections. Our baseline specification is

$$\log k_{i,t+h} - \log k_{i,t-1} = \beta_h^{\text{micro}} \left(\frac{\ell_{i,t-1}-\bar{\ell}_i}{\sigma_{\ell,i}}\right) \xi_{ct}^m + \mathbf{\Gamma}'{}_h \mathbf{Z}_{i,t-1} + \zeta_{ih} + \eta_{sth} + \theta_{cth} + e_{ith}, \tag{2}$$

where k_{it} is the book value of fixed assets (i.e., the nominal capital stock) of firm i at the end of quarter t and $h = [0, 16]$ corresponds to the horizon over which we estimate differential responses of capital to monetary policy. ξ_{ct}^m are the high-frequency identified, information-effect adjusted announcement surprises for the US (1990-2019), which we used earlier in Section 2, and the euro area (2000-2019). c denotes the country in which firm i is located. We use the euro area shocks for firms from all its member countries.

Because we do not observe firm-level capital expenditures, the dependent variable in Equation (2) is the change in the capital stock. As we include sector-by-time and country-by-time fixed effects (η_{sth} and θ_{cth}), which absorb any variation that is common in time (within sectors and countries) such as capital depreciation and capital price changes, differences in the response of capital identify differences in the response of investment to monetary policy. These fixed effects additionally control for unobserved heterogeneity across sectors and countries, such as business cycle conditions or sector-specific nominal rigidities. Because of these time effects, we cannot estimate the average response to monetary policy shocks, but rather, only identify the differential effects by leverage with the coefficient β_h^{micro}.

To assess how the response of investment differs along the dimension of firms' leverage ℓ_{it}, we interact it in lagged and standardized form with the monetary policy surprises, as in the previous section. By demeaning leverage within the firm, we exploit only within-firm variation in leverage to identify β_h^{micro}.[11] This approach ensures that the outcome is not affected by permanent heterogeneity in the responsiveness to monetary policy shocks across firms. The estimated coefficient of interest is $\hat{\beta}_h^{\text{micro}}$, which estimates the differential cumulative semielasticity of capital between quarters t and $t+h$ with respect to the monetary policy shock in t for a standard deviation of leverage. Positive values indicate that high-leverage firms increase their capital stock relative to low-leverage firms when interest rates increase. If the average firm reduces investment after a contractionary monetary policy shock, this means that high-leverage firms are less responsive.

We include a vector of lagged control variables $\mathbf{Z}_{i,t-1}$ to account for other determinants of firms' investment. These are the firm's leverage, the log of its total assets, sales growth, its ratio of current to total assets, and its standardized measure of leverage interacted with quarterly GDP growth of the US or the euro area, depending on where the firm is domiciled.

3.2 Data

We use balance sheet and revenue statement data on publicly listed nonfinancial firms provided by LSEG, formerly Refinitiv. We download data on firms with headquarters in the US (in USD, starting in 1992q2) and in euro area countries (in EUR, starting in 2002q1). The main variables of interest are fixed assets (or capital k_{it}) and leverage (ℓ_{it}), which we define as total liabilities relative to total assets at the end of period t. As in Section 2, we use the broadest possible definition – including debt securities, bank loans and mortgages and other forms of credit such as bills payable – in our baseline measure of leverage. Nevertheless, we will establish the robustness with respect to narrower definitions in Section 4. While we have no data on the terms of these liabilities, we do have information on nominal sales and number of workers. Particularly in some European countries (e.g. France and Italy), it is common even for large corporations to report their financial results semiannually, which is additionally complicated by the fact that some firms change their reporting frequency over time. To nevertheless include these firms in our data, we apply the most conservative principles. Namely, if we only have semiannual data for a given year and firm, we divide flow variables such as sales equally among the quarters in a half year and set the end-of-quarter stock variables of the unobserved quarterly balance sheet to their lagged values.

The data sample is selected to consist of firms with a market capitalization above the median in the respective market, which is approximately 62 million USD and 52 million EUR, respectively. This sample selection ensures that the data is more balanced and the measure of leverage is more reliable, as noisy leverage ratios are quite common for firms below this threshold. To the

[11] Graham and Leary (2011) show that approximately 60% of the variation in leverage is due to to between-firm variation rather than within-firm variation. We exploit only the remaining 40% of the variation for identification.

resulting 4,660 firms, we apply the following exclusion criteria: i.) We disregard the less than 1% of firms with an average leverage higher than 150%. ii.) Approximately 17% of firms are from the real estate and utilities sectors or are fintech firms that are classified as tech firms by LSEG but are actually financial firms. iii.) We drop firms domiciled in Ireland, as these firms exhibit strong fluctuations in capital for reasons that are unrelated to monetary policy. iv.) Finally, we exclude firms with missing observations or no variation within the sector-time and country-time cells. This leaves a sample of ca. 2,800 firms, of which 1,800 are from the US and 1,000 are from the euro area (see Figure A1(a) for details). Importantly, our sample firms is a highly selected sample of large, public firms. Although these firms have an important role in determining aggregates, this selection is an important consideration for making any comparison between firm-level and time series estimates. We will discuss this topic in detail in Section 6.

The sample covers a sizeable share of the private sector in the US and the euro area. For example, total employment of all US firms amounts to over 31 million workers – over a fifth compared to total employment in the private nonfarm business sector – and for the euro area firms, we count a total of 16 million workers. We cover a substantial portion of employment in all major production sectors, even though manufacturing and technology sectors are overrepresented and service sectors are somewhat underrepresented (see Figure A4).[12] For the US, we can compare the sum of balance sheet items of the US firms in our sample to the aggregate in the financial accounts. On average over the sample, our firms represent approximately 25% of assets and approximately 35% of liabilities, and these shares are increasing over time (see Figure A1(b) for details).

The average ratio of liabilities to assets across our firms is approximately 55%. This is somewhat higher than at the aggregate level, where we showed in Figure 1 that average leverage with the same definition was 46%. The reason is that leverage is increasing in firm size[13], and our firms largely represent large, public firms. The interquantile (-decile) range of leverage is approximately 30pp (60pp), making leverage a potentially large source of cross-sectional heterogeneity in the firm data. Even within firms, however, the median standard deviation of leverage is approximately 11pp. This compares to the 3pp standard deviation at the aggregate level (see Section 2.2 for details), which shows that a substantial portion but not all of the firm-level time variation washes out in the aggregate.

Table A4 shows key moments of the leverage distribution by region. A few observations are noteworthy. With 52% in the US and 59% in the euro area, leverage is on average higher in the euro area. Most of this gap persists if we control for time and sector fixed effects. At the same

[12]LSEG assigns each firm to one of 9 broad economic sectors (basic materials, consumer cyclicals and non-cyclicals, energy, healthcare, industrials, real estate, technology, and utilities) as well as a more granular industry definition. To make the representation of the firms comparable to the national accounts, we match each of the more detailed industries in the data to the closest possible 2-digit NAICS industry code, and in the case of manufacturing and retail, to 3-digit codes as well (e.g. chemical manufacturing or food and beverage retailers). Figures A2 and A3 in the appendix show the distribution of sectors and NAICS industries of our data.

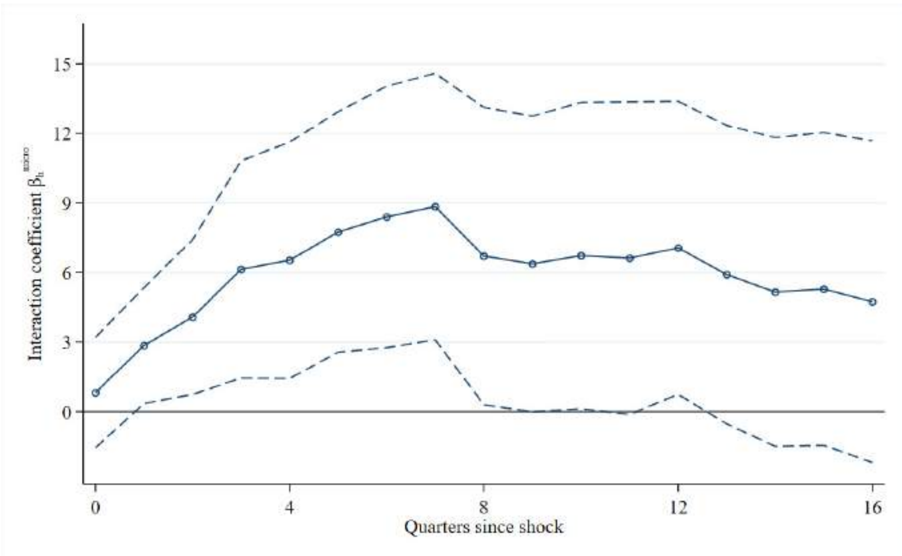
[13]We show this to be the case across firms in our data in Figure A5. Graham and Leary (2011) also document a positive correlation between firm size and leverage, although they also find that the firms with the highest leverage are often young and small. These firms are likely not in our data.

time, within-firm variation of leverage is higher in the US. The median standard deviation of leverage is approximately 13pp in the US and only 8pp in the euro area. Additionally, euro area firms have less dispersed sales growth, investment and operating margins (measured as EBIT divided by sales). In terms of time trends, in the US, the distribution of leverage is shifted up by a few percentage points in the later part of the sample, whereas it is roughly stationary among euro area firms (see also Figure A6). Due to these different properties, data on euro area firms provide a valuable extension of data on US firms, for which OW20 have shown that high-leverage firms respond less to monetary policy shocks.

3.3 Result

Figure 3 shows that estimates of β_h^{micro} are statistically significantly positive for up to 12 quarters after the shock. Thus, relative to low-leverage firms, high-leverage firms *increase* investment in response to a contractionary monetary policy shock. At the peak effect in $h = 7$, a firm's capital has a 9pp higher (less negative) semielasticity to a monetary policy shock if its leverage is one standard deviation higher than usual. For the median firm in our sample, a standard deviation is approximately 10pp. Based on these values, we would expect the medium-term semielasticity of capital to monetary policy shocks to be 0.9pp higher for each percentage point in additional ex-ante leverage. This value compares to the 1-2pp lower (more negative) capital response we have imputed based on macro elasticities and shown in Figure 2.

Figure 3: Difference of micro elasticity between high- and low-leverage firms



Notes: Estimation results of panel local projections, see Equation (2). The coefficients $\hat{\beta}_h^{\text{micro}}$ for the interaction of a standardized measure of firm-specific leverage with the (contractionary) monetary policy shock are shown. The estimation sample consists of ca. 2,800 firms from the US (1992-2019) and the euro area (2002-2019). We use the Jarociński and Karadi (2020) monetary policy shocks identified for the respective currency area of the firms' headquarters. Standard errors are clustered by firm and quarter. We depict the 95% confidence intervals as dashed lines.

Our estimates must be interpreted relative to the average response of firms' capital to monetary policy shocks. However, the mean response cannot be estimated with Equation (2) because it is absorbed in the time-specific fixed effects η and θ, which are crucial for the identification of $\hat{\beta}_h^{\text{micro}}$. In Appendix B.5 we relax this assumption and estimate the average response of capital as approximately -5%, although the estimate is not statistically significant at conventional levels, whereas the interaction coefficient of leverage is both statistically and economically significant.

Our results provide corroborating evidence of the central empirical result of OW20, despite several considerable differences in the specification, data sample and shock series. They interpret the higher semielasticity of high-leverage firms through the lens of a New Keynesian model with heterogeneous firms, which we outline in more detail in Section 5.1, but briefly summarize now in order to have a framework to interpret the estimated micro elasticities. In the OW20 model, firms can finance new investment using internal or external finance. In the event of a default, whose probability increases with leverage, external lenders recover only a fraction of the firm's capital stock. This gives rise to an external finance premium, which is increasing in leverage. That is, firms with high net worth (and low leverage) can fund additional investment at relatively low cost, whereas firms that are already highly leveraged face higher costs for additional borrowing. In other words, the marginal cost curve is convex in investment, given the current capital stock. Higher real interest rates due to a contractionary monetary policy shock imply a higher discount rate of future cash flows and thus a lower discounted return on investment. With a monetary policy shock, the marginal benefits of investment decrease. Hence, firms reduce their investment in response. High-leverage firms, however, operate on the steep part of the marginal cost curve and only reduce their investment by a little. Relative to low-leverage firms, high-leverage firms increase their investment.

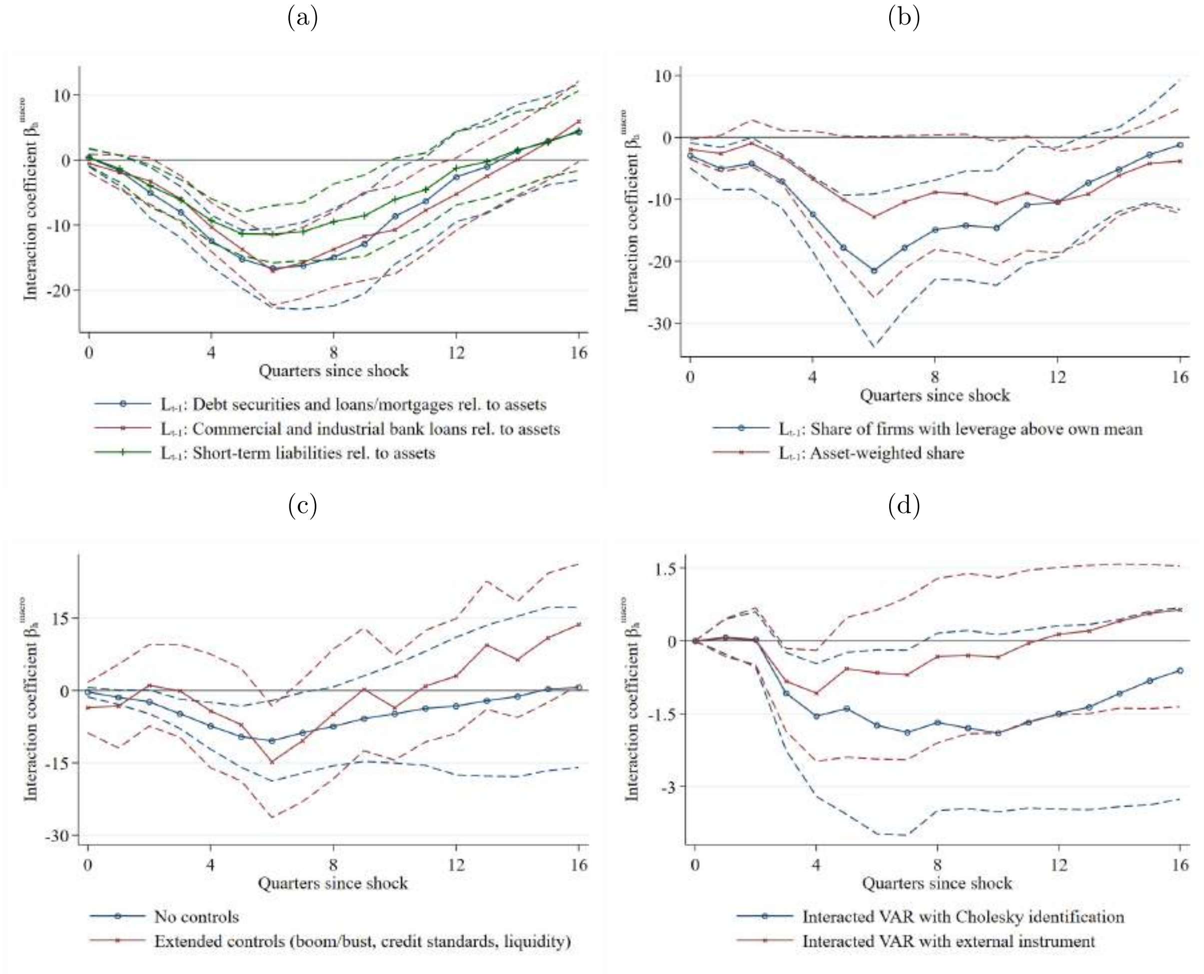
4 Robustness

We have so far documented a micro-macro conundrum: While the firm-level decline of capital is smaller if a firm has high leverage, aggregate capital falls more if many firms have high leverage. This section shows that both pieces of evidence are robust in terms of definitions of leverage and a variety of regression specifications.

4.1 Robustness of macro elasticity

Some robustness checks for $\hat{\beta}_h^{\text{macro}}$ are presented in Figure 4. First, in Panel (a), we use narrower definitions of liabilities when computing leverage (all retrieved from aggregate statistics and relative to total assets) in the interaction term. These alternative measures are i.) the sum of debt securities and loans and mortgages, which together make up approximately half of the broader measure of liabilities used in the main result, ii.) commercial and industrial bank loans from a bank survey and iii.) short-term liabilities regardless of the source of funding. As before, all measures of leverage are standardized by their historical means and standard deviations. The pairwise correlations with the broader measure from the main result are 0.64, 0.11 and

Figure 4: Macro elasticity: Robustness



Notes: The baseline result is depicted in Figure 2 and estimates the local projections described in Equation (1). The top two panels use alternative measures of corporate leverage as the interaction variable. Robustness is also established with respect to the control variables (c) and the specification as a nonlinear VAR spanning a larger data sample (d). The latter is described in Section B.2 in the appendix.

0.04, respectively. Despite relatively weak correlations with the broader measure of leverage, the differential response of investment to changes in the short-term policy rate is more negative with high leverage in all three cases.

Second, we use measures computed from the micro data as the state variable. In our estimation of the micro elasticity, leverage enters in deviation from the firms' own means. If a firm has higher-than-usual leverage, its investment becomes less responsive to monetary policy. If this fact translated directly to the aggregate, then investment would respond less to monetary policy if many firms had leverage above their own mean. In Panel (b) of Figure 4, we show estimates from nonlinear local projections in which L_t is the share of firms with leverage above their own mean. The estimated interaction coefficient $\hat{\beta}_h^{\text{macro}}$ remains negative, even though these measures, which are depicted in Figure A6 in the appendix, have only limited correlation with the baseline L_t (0.4 and 0.18, respectively).

Third, we show that our results are not qualitatively sensitive to the control variables $\mathbf{Z}$ used in Equation (1). On the one hand, we drop control variables entirely. On the other hand, we include an array of covariate cross-terms of conditions that might potentially confound our results. For example, corporate leverage is somewhat countercyclical and the investment effects of monetary policy might differ between recessions and expansions for reasons other than the levels of leverage. To account for this, we include the lagged output gap (CBO estimate) and the lagged GDP growth, both interacted with the federal funds rate, as additional controls. Additionally, there may be a concern that corporate leverage correlates with leverage in the household sector. In that case, our results might, for example, be driven by the fact that households' final demand responds more or less to monetary policy shocks (see, e.g. Cloyne et al. (2020), Flodén et al. (2020), Holm et al. (2021) or Alpanda et al. (2021)) and firms' investment responds to that demand in final consumption rather than funding costs as such. We include interaction terms of the federal funds rate with the loan-to-value ratio for household mortgages and with the ratio of consumer bank loans to GDP. Coimbra and Rey (2024) provide stylized facts that imply that the elasticity of bank credit to funding costs varies with the level of interest rates, a channel that we can proxy by interacting the federal funds rate with itself. We also include the ratio of liquid assets, relative to all assets, of the corporate business sector as an additional control variable, given micro evidence from Jeenas (2024), as well as a measure of unit profits. Regardless of whether or not we include these additional covariate cross-terms, we find that firms' investment responds significantly more to short-term interest rates when corporate leverage is high (Figure 4(c)).

The last two checks shown in the last panel of Figure 4 restrict the dynamics of the parameters somewhat by estimating an Interacted VAR. An Interacted VAR is a parsimonious way to implement nonlinearity in a VAR, which is described in detail in Appendix B.2. We implement two versions: One where monetary policy shocks are identified using a Cholesky decomposition and one in which the Jarociński and Karadi (2020) monetary policy surprises are used as an external instrument on the residuals of the federal funds rate in the VAR, as in Gertler and Karadi (2015). This approach permits the identification sample to be shorter than the sample for the estimation of the dynamic correlations, which allows us to include the full period from 1973q1 to 2019q4 in the estimation of both Interacted VARs. The figure shows the difference between generalized impulse response functions when the baseline measure of aggregate corporate leverage is above or below the median of its historical distribution. For both identification strategies, the difference is statistically significantly negative.[14]

In results shown in the appendix, we conduct further sensitivity checks with respect to the instrument for changes in the federal funds rate chosen. For example, our result that investment responds more to monetary policy changes is even quantitatively similar if we use Romer and Romer (2004) shocks, whose standard deviation is more than three times as large as high-

[14] As expected, the magnitude of the difference is different in the Interacted VARs than in the other specifications. While all previous results have shown the differential effect of monetary policy if ex-ante leverage is one standard deviation higher, the Interacted VAR results show the difference between the average generalized IRF in quarters with high leverage vs. the average generalized IRF in quarters with low leverage.

frequency surprises by Jarociński and Karadi (2020) for the overlapping period. The estimated interaction term is still statistically significantly negative, regardless of whether we implement it as an IV regression as above, or whether we estimate interacted reduced-form regressions.

Another concern could be that the reaction function of monetary policy and thus the identified monetary policy shocks we use are systematically related to leverage, which could bias our estimates. For example, there may be no contractionary monetary policy shocks when leverage is high. However, we show in Figure B2 in the appendix that historically, there is no correlation between the levels of corporate indebtedness and monetary policy decisions, neither with raw changes in interest rates nor with the identified monetary policy shocks.

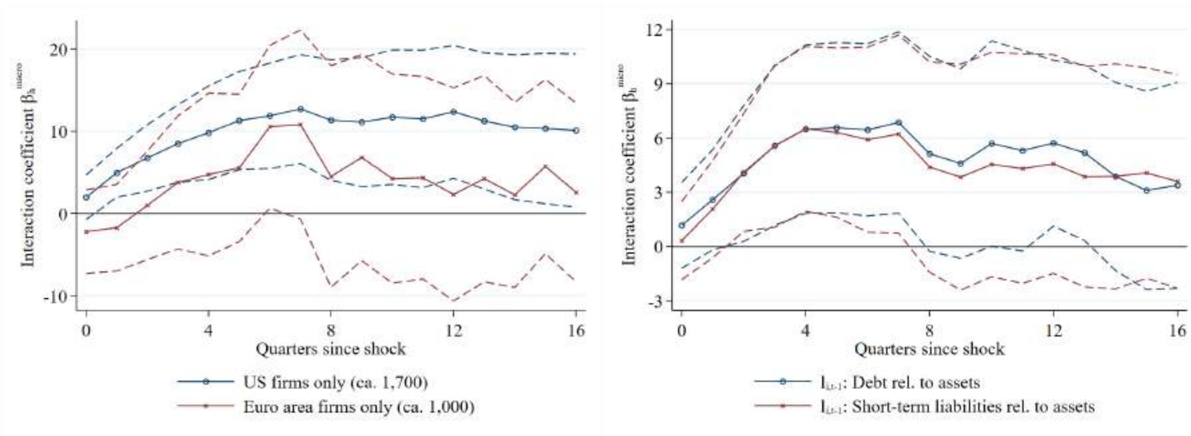
Ultimately, in Appendix B.4, we repeat the analysis for the euro area. The results are less conclusive than for the US, but the point estimate of $\hat{\beta}_h^{\text{macro}}$ for the medium-run h is negative even with these shorter and noisier time series.

4.2 Robustness of micro elasticity

The empirical result that firm-level leverage predicts a less negative reaction of capital after contractionary monetary policy shocks holds for various modifications as well. Figure 5(a) shows the coefficients when separately estimating Equation (2) for the US and the euro area. The latter makes up less than a third of the data and covers firms based in 11 euro area member states, which is why we still include country-time fixed effects in that specification. Euro area firms have on average higher but less volatile leverage. The interaction coefficients between monetary policy shocks and leverage are less precisely estimated, but clearly positive in the medium run.

Figure 5: Micro elasticity: Robustness

(a) (b)



Notes: The baseline result is depicted in Figure 3 and estimates the local projections described in Equation (2). Panel (a) shows estimates based on US and euro area panels separately, whereas (b) uses alternative, but still firm-level and standardized, measures of leverage as the interaction variable. See Appendix B.5 for further robustness tests of the micro elasticity.

In Figure 5(b) we plot the results of the main alternative definitions of $\ell_{i,t}$. The blue lines show estimates of $\hat{\beta}_h^{\text{micro}}$ when leverage is defined as debt over assets, which is a narrower measure than liabilities over assets and includes only debt securities and bank loans and mortgages. For the red lines, we use only short-term liabilities to compute leverage. Even though the correlations with our baseline measure of leverage are only 0.7 and 0.45, respectively, the estimates are still statistically significantly positive.

In the appendix, we provide an array further robustness checks (see Appendix B.5 for a complete list). Among other things, we account for the fact that for most firms, borrowing contracts based on cash flow constraints are the more relevant source of funding than asset-based borrowing constraints (Lian and Ma, 2021). The OW20 result holds even when leverage is defined as the ratio of liabilities or debt to earnings. The interaction coefficient is positive if we use non-standardized (but winsorized) measures of leverage, too. Additionally, we show that the heterogeneity of the estimated response to monetary policy assigned to leverage in our estimation is not driven by differences in liquid asset holdings or firm age. Lakdawala and Moreland (2021) argue that the differential effect we find reversed in the period after the Great Recession. According to our estimations, we cannot rule out a somewhat weaker β_h^{micro} after the Great Recession, but we do not find evidence that its sign reversed. The main results are also confirmed with alternatives to the high-frequency monetary policy surprises.

5 A general equilibrium explanation

So far, we have shown that in the micro data, firms with high leverage decrease investment less after a monetary policy shock – confirming the result reported by OW20 –, while in the aggregate, high leverage leads to stronger responses of monetary policy. In this section, we provide an explanation that reconciles both empirical findings, while adhering to the OW20 modelling framework. In a nutshell, the difference between micro and macro elasticities is that the micro elasticity estimation includes time-specific fixed effects, which are crucial for identification, but also absorb any potential general equilibrium effects in response to the monetary policy shock, which depends on the cross-sectional distribution of firms. We first briefly describe their model and discuss how it results in effects of monetary policy consistent with the micro evidence. Subsequently, we present our explanation that leads to impulse response functions of investment that differ depending on the level of leverage in the aggregate economy. Finally, we provide evidence in favor of our hypothesis.

5.1 Model

5.1.1 Investment block

Production firms. There is a fixed mass of heterogeneous production firms; time is discrete and runs forever. Each firm $i \in [0, 1]$ uses the production function $y_{it} = z_{it}(\omega_{it}k_{it})^{\theta}l_{it}^{\nu}$, where

k_{it} and l_{it} correspond to the firm's capital stock and labor input, respectively, to produce an undifferentiated good y_{it}. Inputs are purchased at their relative prices q_t (for capital) and w_t (for labor).[15] Production is subject to decreasing returns to scale; i.e., $\theta + \nu < 1$. Firms experience two types of idiosyncratic shocks: ω_{it} is an i.i.d. capital quality shock log-normal distribution truncated at a maximum of 0 and z_{it} is a total factor productivity (TFP) shock that follows a log-AR(1) process with innovations $\varepsilon_{it} \sim N(0, \sigma^2)$.

In each t, a mass of new firms $\bar{\mu}_t$ enter the economy endowed with k_0 units of capital and no debt, replacing the mass of firms that exit either due to an exogenous shock or an endogenous exit decision. Subsequently, idiosyncratic shocks to capital quality and TFP are realized. Each firm produces the undifferentiated good and receives an exogenous shock to exit the economy with probability π_d afterwards. The remainder, with mass $(1 - \pi_d)$, decides whether or not to default. In the case of default, a fraction of the firm's capital stock is recovered by the lenders. To continue operations, firms must pay back the face value of outstanding debt, b_{it} and a fixed operating cost ξ in units of the final good. They hire labor l_{it} at the real wage w_t and sell the output to retailers at a relative price p_t. New capital $k_{i,t+1}$ is purchased at relative price q_t. To finance investment, firms can either issue new nominal debt, which is offered at a firm-specific price schedule $Q_t(z_{it}, k_{i,t+1}, b_{i,t+1})$, or use internal finance by lowering dividend payments d_{it}, where $d_{it} \geq 0$, which is the key financial friction in the model.

The firm's state variables are its productivity z and its net worth n, defined as $n = \max_l \, p_t z(\omega k)^\theta l^\nu - w_t l + q_t(1-\delta)\omega k - b\frac{1}{\Pi_t} - \xi$. These are the real resources of the firm, i.e., its current operating profits and the liquidation value of its capital stock net of real borrowing (where Π_t is the aggregate inflation rate of the final good P_t) and the fixed cost of operating. Conditional on continuing, the real equity value $v_t(z, n)$ solves the Bellman equation (3), where $\hat{n}_{t+1}$ is the net worth implied by the chosen future k' and b'.

$$
\begin{aligned}
v_t(z,n) = & \max_{k',b'} \; n - q_t k' + Q_t(z,k',b')b' \\
& + \mathbb{E}_t\big[\Lambda_{t+1}(\pi_d \chi^1(\hat{n}_{t+1}(z',\omega',k',b'))\hat{n}_{t+1}(z',\omega',k',b') \\
& \times (1-\pi_d)\chi^2_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b'))v_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b')))\big] \\
& \qquad \text{s.t.} \qquad n - q_t k' + Q_t(z,k',b')b' \geq 0
\end{aligned}
\tag{3}
$$

Lenders. A financial intermediary lends resources from the representative household to firms with a firm-specific price schedule $Q_t(z, k', b')$. In the event of a firm's failure to repay the loan in the next period, the lender recovers a fraction α of the market value of the firm's capital stock. This default risk is reflected in the debt price schedule.

[15] All prices are expressed relative to the price of the final good P_t.

$$
\begin{aligned}
Q_t(z,k',b') = &\mathbb{E}_t\Bigg[\Lambda_{t+1}\frac{1}{\Pi_{t+1}}\Bigg(1-(1-(\pi_d\chi^1(\hat{n}_{t+1}(z',\omega',k',b'))\\
&+(1-\pi_d)\chi^2_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b'))))\\
&\times\left(1-\min\left\{\frac{\alpha q_{t+1}(1-\delta)\omega'k'}{b'/\Pi_{t+1}},1\right\}\right)\Bigg)\Bigg]
\end{aligned}
\tag{4}
$$

5.1.2 Remainder of the model

Retailers and final goods producer. A retailer $j \in [0,1]$ produces a differentiated variety of the final good using producers' outputs y_{it} as the only input. The relative price of the variety is subject to quadratic adjustment costs. By aggregating retailers and final good producers, the New Keynesian Phillips Curve (NKPC) is

$$
\log \Pi_t = \frac{\gamma-1}{\varphi}\log\frac{p_t}{p^*} + \beta\mathbb{E}_t \log \Pi_{t+1}, \tag{5}
$$

where γ is the elasticity of substitution between varieties, $p^* = \frac{\gamma-1}{\gamma}$ is the steady state output price of differentiated varieties and φ governs price adjustments costs.

Capital good producer. New aggregate capital K_{t+1}, which is aggregated across individual firms ($K_t = \int k_{it}di$), is produced by a representative capital good producer who turns I_t units of final goods into new capital. Crucially, if many firms want to expand their capital stock, the relative price of capital q_t rises with an elasticity of $\frac{1}{\phi}$, according to the following supply schedule:

$$
q_t = \left(\frac{I_t/K_t}{\hat{\delta}}\right)^{1/\phi}, \tag{6}
$$

where $\hat{\delta}$ is the steady state reinvestment rate. ϕ governs the degree of aggregate capital adjustment frictions and influences the variations in q_t, which is a crucial component of our hypothesis.

Monetary authority. The central bank follows a standard Taylor rule for the nominal interest rate $\log R_t = \log\frac{1}{\beta} + \varphi_\pi \log \Pi_t + \xi^m_t$, where φ_π is the reaction coefficient to inflation and the monetary policy shock ξ^m_t is drawn from the distribution $N(0,\sigma^2_m)$.

Representative household. The economy is inhabited by a standard representative household, which owns all firms in the economy. The household maximizes $\mathbb{E}_0\sum_t^\infty \beta^t(\log C_t - \psi L_t)$, where β defines the discount factor and ψ denotes the disutility of labor.

5.1.3 Firm-level decision rules

Equation (7) characterizes the optimal choice of investment k' and borrowing b' of production firms. The left- and right-hand sides of Equation (7) represent the costs and benefits of a marginal unit of capital, respectively.

$$
\begin{aligned}
\Big(q_t - \varepsilon_{Q,k'}(z,k',b')\frac{Q_t(z,k',b')b'}{k'}\Big)&\frac{R_t^{sp}(z,k',b')}{1-\varepsilon_{R,b'}(z,k',b')} \\
&= \frac{1}{R_t}\mathbb{E}_t[MRPK_{t+1}(z',k')] \\
&+ \frac{1}{R_t}\frac{\mathbb{C}ov_t(MRPK_{t+1}(z',\omega'k'),1+\lambda_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b')))}{\mathbb{E}_t[1+\lambda_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b')))]} \\
&- \frac{1}{R_t}\mathbb{E}_{\omega'}[v^0_{t+1}(\omega',k',b')g_z(\underline{z}(\omega',k',b')|z)\hat{\underline{z}}_{t+1}(\omega',k',b')]
\end{aligned}
\tag{7}
$$

Marginal costs are the product of two terms, the first of which is the relative price of capital q_t net of changes in interest expenditures through adjusted capital and thus default risk, where $\varepsilon_{Q,k'}$ is the sensitivity of the debt pricing schedule to investment. The second term of the product, which turns out to be crucial for the heterogeneous transmission of monetary policy, consists of the spread of borrowing costs over the risk-free rate R_t^{sp} and its elasticity with respect to borrowing $\varepsilon_{R,b'}$.

This product makes the marginal cost of additional capital, given productivity, convex. When capital is chosen to be low, the marginal cost curve is flat, as firms have enough cash to not be considered risky. To increase capital substantially, and given the financial frictions, the borrowing required to finance this additional capital increases firms' risk of default and therefore borrowing costs. The marginal cost curve thus becomes steeper in this region.

The marginal benefits of investment, on the other hand, can be expressed as three separate terms: i.) The expected discounted return on capital, which decreases when the real interest rate rises because it is discounted more heavily, ii.) the covariance of the return on capital with the firm's shadow value of resources (λ_{t+1}) and iii.) the change in the default probability.[16] The marginal benefit curve is downward-sloping in additional investment due to diminishing returns to capital.

Firms operating in the steep part of their marginal cost curve can be considered "risky constrained", and because of the financial frictions, they operate at a scale below their optimal level of capital. Such firms include particularly young firms, as firms start with initial capital below the optimum and borrow to reach their optimal scale, after which they pay down their debt.

5.1.4 Channels of monetary transmission

To assess the benchmark effects of an unexpected monetary policy shock ξ_t^m in this model, we set all model parameters to the values as in OW20, the full list of which is presented in Table C1 in the appendix. Stylized marginal cost and marginal benefit curves as a function of capital accumulation k' and their shifts after a contractionary monetary policy shock are illustrated in

[16] $\underline{z}_t(\omega,k,b)$ denotes the productivity threshold at which the firm defaults, $g_z(z'|z)$ is the density of z' conditional on z and $v_t^0(\omega,k,b)\equiv v_t(\underline{z}_t(\omega,k,b)$, and $\hat{n}_t(\underline{z}_t(\omega,k,b),\omega,k,b))$ is the firm's value evaluated at the default threshold. Furthermore, $\hat{\underline{z}}_{t+1}(\omega',k',b')\equiv\frac{\partial\underline{z}_{t+1}(\omega',k',b')}{\partial k'}+\frac{\partial\underline{z}_{t+1}(\omega',k',b')}{\partial b'}(q_t-\varepsilon_{Q,k'}\frac{Q_t(z,k',b')b'}{k'})\frac{R_t(z,k',b')}{1-\varepsilon_{R,b'}(z,k',b')}$.

the top two panels of Figure 6.

An increase in the real interest rate decreases the discounted return on capital, thus shifting the marginal cost curve downwards (see green arrow). The effect of this shift on the choice of capital k' depends on the slope of the marginal cost curve. For the high-leverage firm, the decrease in capital is smaller than for the low-leverage firm. OW20 find that the second and third term of the marginal benefit curve – see the right-hand side of Equation (7) – are not quantitatively important.

The different components reflected in the marginal cost curve react to monetary policy as well. A contractionary monetary policy shock leads to a decrease in q_t due to a decline in (partial equilibrium) investment demand. This is shown by the purple arrow in Figure 6. At the same time, however, there are additional interest rate expenditures since, ceteris paribus, lower firm collateral increases expected losses for lenders due to firm default (yellow arrow). Additionally, interest rate spreads following the adjustment of capital and external debt increase because the firm's collateral value decreases (blue arrow). The latter two effects impact the capital of low-leverage firms to a greater extent, but under the OW20 parameter calibration, the overall impact of monetary policy shocks is larger on capital for low-leverage firms than for high-leverage firms. This is reflected in our positive *between-firm* coefficient β_h^{micro}.

5.2 State-dependent monetary policy effects within the OW20 framework

We now explore how this *between-firm* heterogeneity can be consistent with the opposite-signed *between-states* heterogeneity, which we documented in Section 2. Instead of comparing states within the above-presented OW20 economy, we proceed by modeling a second economy in which we vary only a single parameter to generate a different level of aggregate leverage. Subsequently, we shock both economies in their respective steady states with the same one-time unexpected monetary policy shock and compare the respective perfect foresight transition paths of the two initial conditions.[17]

5.2.1 Simulation of a high- and a low-leverage economy

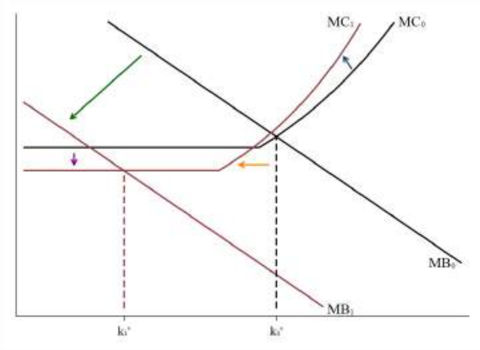
The OW20 parameterization of the model leads to an aggregate leverage of 49%, which is approximately one standard deviation above the historical mean of 46% observed in the time series (see Section 2.2). We therefore refer to it as the high-leverage economy. For the counterfactual low-leverage economy, we vary only one of the fixed parameters. An increase in the initial capital endowment of new entrants k_0 decreases aggregate leverage in the OW20 model. In the model, firms get leveraged since they are born with a capital stock that only allows them to

[17] In our assessment of the aggregate state dependence in Section 2, we included an array of control variables to account for the state of the business cycle. The historical variation in aggregate leverage, of course, not only reflects the variation in steady states but also is an endogenous reaction to shocks. However, by controlling for the state of the business cycle, we attempt to hold these factors fixed, effectively comparing the impulse response functions of two similar economies that vary only in their level of leverage, as in our modeling strategy.

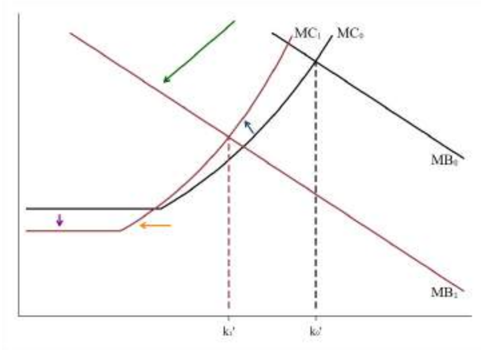
Figure 6: Effects of a contractionary monetary policy shock

Effects in high-leverage economy

(a) Low-leverage firm

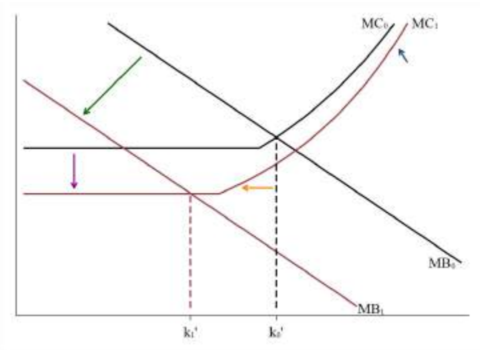


(b) High-leverage firm

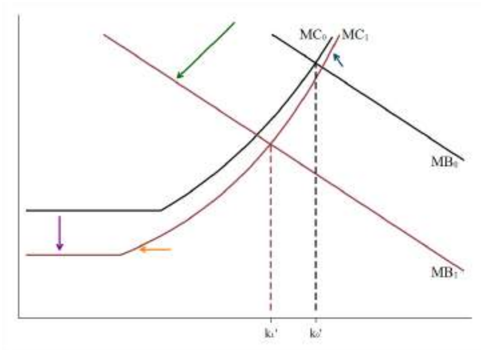


Effects in low-leverage economy

(c) Low-leverage firm



(d) High-leverage firm



Notes: Simulations of a contractionary monetary policy shock (red curves) on the marginal costs and benefits of capital accumulation in the OW20 model, see Equation (7). We show two stylized firms that differ in their risk/leverage ℓ_{it} (left and right). The two firms are part of a fixed mass of heterogeneous production firms, and the top and bottom panels differ in terms of the distribution of leverage among these firms (L_t). If all other firms have low leverage and reduce investment demand substantially after a contractionary monetary policy shock, the relative price of capital decreases more strongly (purple arrow), which dampens the response of both firms.

operate below the optimal capital implied by their productivity and pay back debt to reduce risk thereafter. They reach their optimal size more quickly by borrowing and therefore do so particularly when young.

By endowing newly born firms with a higher k_0, we allow them to reach their optimal capital more quickly and with a lower default probability. Although this approach reduces leverage disproportionately for the young firms, as shown in Figure C1 in the appendix, it reduces leverage slightly for the entire age distribution. The lower average leverage of firms contributes to lower average spreads for firms in the low-leverage economy and reduces the number of "risky constrained" firms (see Table 1).

An alternative way to simulate a counterfactual economy with lower aggregate leverage is to decrease the probability of firms receiving i.i.d. exit shocks. This lowers the turnover of firms in the economy and shifts the age distribution to older, more productive firms. Both alterations are

Table 1: Alterations of model parameterizations and resulting aggregate leverage

Parameter	High L: OW20	Low L (I): Higher initial k	Low L (II): Lower exit rate
Initial capital stock, k_0	0.18	0.33	0.18
Exogenous exit rate, π_d	1.47%	1.47%	1.31%
Mean gross agg. leverage	49%	46%	46%
Share of risky constrained	64%	55%	57%

Notes: Variations of single parameters to decrease the average steady state level of leverage. All other parameters are calibrated as in Table C1.

summarized in Table 1. While the first changes the initial distribution of leverage conditional on age, the second holds it constant and instead changes the age composition to achieve lower aggregate leverage as an initial condition prior to the shock.

5.2.2 Comparison of impulse response functions

Figure 7(a) plots the responses of aggregate investment after a one percentage point increase in the nominal interest rate. Given that nominal interest rate changes move the real interest rate under sticky prices, the left-hand shift of the marginal benefit curve at the firm level leads to a substantial contraction of aggregate investment in the model.

The blue line is equal to the response shown in OW20 (with an aggregate leverage of 49%), and the dashed lines show our alterations with lower aggregate leverage (46%) at the time of the shock. To generate the differential responses in Panel (b), we subtract IRFs from the high-leverage economy in either of our alterations.

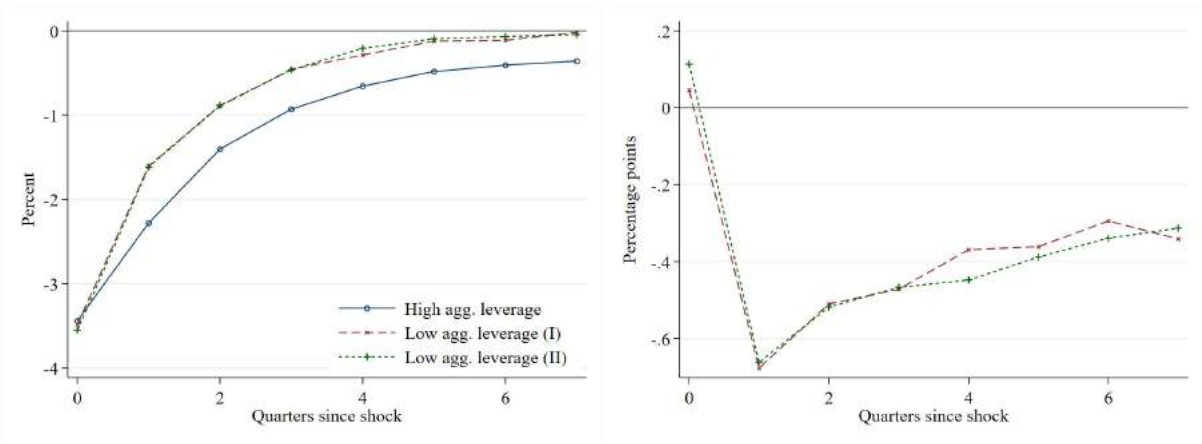
Regardless of which alteration we apply to vary the distribution of leverage at the time of the shock, monetary policy has a larger effect on investment in the high-leverage economy. We emphasize that this effect occurs despite the property of the model that risky firms respond less to monetary policy at the individual level.

5.2.3 Channel decomposition: The role of the relative price of capital

Financial heterogeneity across firms in an economy, as well as across economies with different leverage distributions contribute to varying strengths of different channels of monetary policy to firms' capital choices. We disentangle those channels in the same way as OW20, who feed into the model the path for one price while holding all other prices fixed at steady state. The first and most direct channel is the change in the real interest rate, represented by the leftward shift of the marginal benefit curve in Figure 6 (green arrows). The responses of capital can be heterogeneous across different levels of productivity and preexisting net worths, and we summarize the responses by computing the density-weighted averages above and below the median net worth threshold and average across the productivity grid. The first two bars in

Figure 7: Aggregate investment responses to monetary policy

(a) Aggregate investment response by model (b) Differences



Notes: Aggregate response of investment to contractionary monetary policy shock under different calibrations. "High agg. leverage" shows the results of the OW20 calibration of the model (49%). The dashed lines show alternative calibrations with an aggregate leverage that is more in line with the empirical mean of the time series (46%). The shock is scaled to a 1 percentage point increase in the nominal interest rate in all three models. Panel (b) subtracts the blue line from the dashed lines in Panel (a).

Figure 8(a) show a negative semielasticity of investment to a tightening of monetary policy through the real rate channel. It has a weaker effect on firms with high leverage, i.e., firms with high default risk and low net worth (solid bar), than on firms with low leverage (empty bar). This is the main heterogeneity that the OW20 model rationalizes.

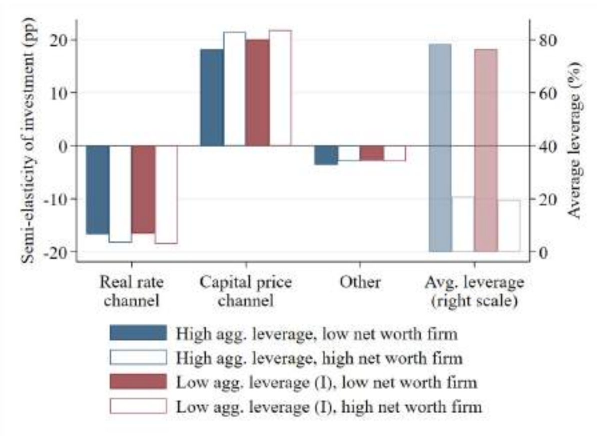
To quantify the strength of the second channel, we feed in the series of the relative price of capital q_t but keep all other prices constant. This channel has two components. On the one hand, higher interest rates lead to lower partial equilibrium investment demand, depressing the price of capital (relative to the sticky-price numéraire) and *ceteris paribus* incentivizing all firms to invest. On the other hand, a lower q_t decreases the recovery value of the lender, resulting in higher risk premia, which discourage investment. The second set of bars in Figure 8(a) are positive, indicating that the incentive-to-invest effect dominates, especially for low-leverage firms. The contribution of all other prices, shown in the third set of bars in 8(a), is relatively small.

To shed light on how aggregate leverage interacts with the strength of these channels, we decompose the same channels in an economy where the initial distribution of leverage is lower due to a parameterization with a higher initial stock of capital when the firm is born. The results are shown using the red bars in Figure 8(a). The following observations stand out. First, the magnitude of the real rate channel is almost unchanged and, as with the blue bars, has a weaker effect on high leverage, low net worth firms. Second and more importantly, the capital price channel is stronger in an economy with lower leverage.

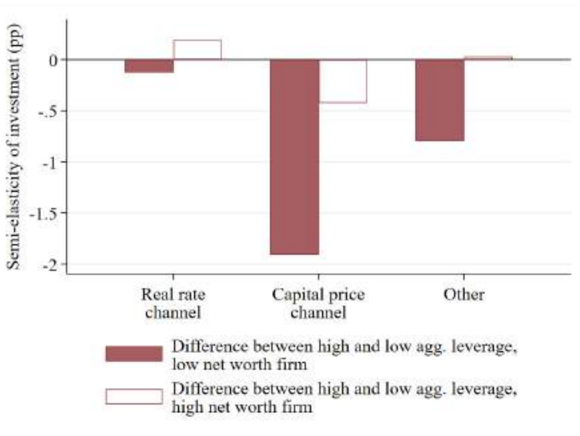
The relative price of capital channel is the most important difference between the original calibration with a relatively high average leverage and our alternative calibration with a lower average leverage, as shown in Figure 8(b). The negative values for this channel show that the muted magnitude of this channel in an economy with many highly leveraged firms leads to a lower-semielasticity of aggregate investment to monetary policy. On the other hand, in an economy where many firms have low leverage and reduce their investment demand substantially after a contractionary monetary policy shock, the relative price of capital decreases. Investment becomes relatively cheap, which provides an incentive for *all* firms to invest more. This effect is so strong that it reverses the micro elasticity.

Figure 8: Decomposition of the semielasticity of capital to monetary policy

(a) Channels by model



(b) Differences



Notes: The semielasticity of capital with respect to a contractionary monetary policy is decomposed into three channels by feeding the response of one variable in the model while holding all other prices fixed. To summarize the high-dimensional responses of firms along the initial net worth distribution and productivity, we compute, for each productivity grid, the density-weighted response for firms below and above the median net worth, and then average across productivities. Low net worth firms have high leverage, and vice versa (see fourth set of bars). Blue is the OW20 parameterization of the model, red bars represent responses following the alteration in which new-born firms start with higher initial capital, leading to a lower steady state aggregate leverage (46% vs. 49%). Panel (b) shows the differences between the blue and red bars of Panel (a).

Figure 8 shows a highly summarized version of the decomposition of transition paths, aggregating over firms below and above the median of the initial net worth distribution and different productivity levels. Figure C2 in the appendix shows the decomposition along a more disaggregated distribution. Additionally, in Figure C3, we show that the same holds in the alternative calibration, where we achieve a lower aggregate steady state leverage by decreasing the exogenous firm exit rate.

We have shown that the micro elasticity – lower leverage firms respond more strongly to monetary policy – and macro elasticity – aggregate investment is more responsive to monetary policy when corporate leverage is high – are not inconsistent with each another, even within the OW20 model. The reason is that the equilibrium price response (for capital) depends on the cross-sectional distribution of leverage at the time of the shock but affects all firms. As it affects all firms' marginal cost of investment equally, it is fully absorbed by the time fixed effects in Equation (2). The results could also be framed in terms of pecuniary externalities (Lorenzoni, 2008, Bianchi, 2011). As firms are atomistic, they do not take into account the effect of their investment demand on the price of capital, which is a determinant of all other firms' investment. Therefore, the distribution of leverage across firms and the resulting heterogeneity in investment demand responses to monetary policy changes the aggregate effects of monetary policy.

5.3 Supporting empirical evidence

We discuss two results implied by the model and our explanation, for which we find empirical support in the data. The first result is that the relative price of capital responds less to a monetary policy shock if the economy is in a high-leverage state. The second result is that the firm-level heterogeneous response to monetary policy is itself a function of the aggregate state of the economy.

5.3.1 The relative price of capital

After a contractionary monetary policy shock, the relative price of capital decreases in the model because demand for capital decreases and the prices of final output goods are sticky. However, the claim at the core of our explanation in Section 5.2 is that the relative price of capital falls less in a high-leverage economy, making it more costly for all firms to invest than in a low-leverage economy. We test this proposition directly with the data.

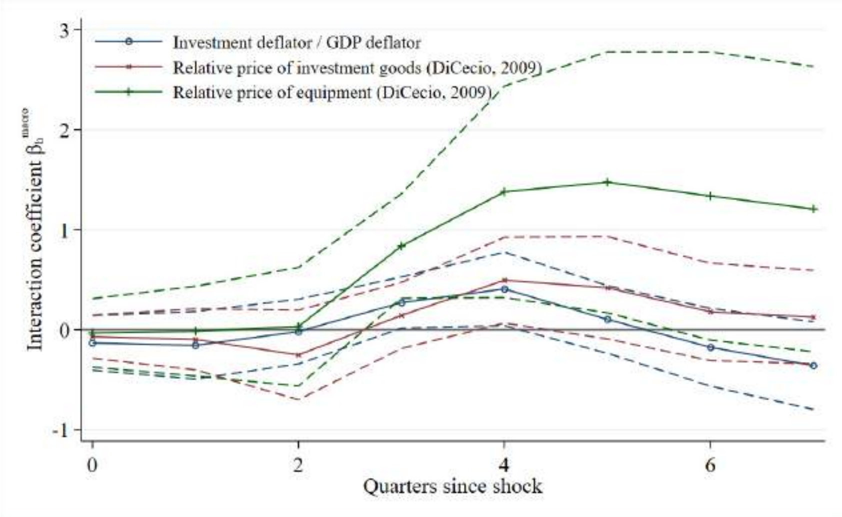
Specifically, we re-estimate our aggregate local projections (Equation (1)), replacing the dependent variable with different measures for the relative price of capital. Figure 9 shows three sets of impulse responses of the state dependence estimated by $\hat{\beta}_h^{\text{macro}}$. These are, most simply, the ratio between the deflators of investment and GDP as a whole and two measures that compare the price of capital with that of consumption goods proposed by DiCecio (2009).[18] In all three cases, the estimated interaction coefficients are positive a few quarters after the shock, showing that – as we claim in our explanation – the relative price of capital falls less after a monetary policy contraction if aggregate leverage is high.

5.3.2 State-dependent heterogeneity of firm-level responses to monetary policy

The second implication of our analysis is that the financial heterogeneity of firm-level responses to monetary policy shocks, which we have estimated with $\hat{\beta}_h^{\text{micro}}$, is itself of a function of aggregate leverage. This implication was already evident in our stylized illustration of the model in Figure 6. The difference in responses between low- and high-leverage firms is larger when most firms belong to the latter group (two top panels) because of a stronger capital price channel. We confirm this result in the quantitative models by simulating a panel of firms subject to monetary policy shocks (innovations to the Taylor rule) and running a regression equivalent

[18]DiCecio constructs the deflator for investment goods by updating annual quality-adjusted deflators of investment subcomponents fitted by Cummins and Violante (2002). The annual deflators are interpolated to the quarterly frequency with the help of quarterly deflators from NIPA data. The resulting investment deflator is divided by the consumption deflator to obtain the relative price of capital.

Figure 9: Differential response of the relative price of capital



Notes: Interaction coefficient $\hat{\beta}_h^{\text{macro}}$ in Equation (1) between the standardized measure of corporate leverage with a (contractionary) monetary policy shock. The dependent variable is replaced by different definitions of the relative price of capital. The 95% confidence intervals based on HAC standard errors are shown as dashed lines.

to our firm-level local projections (Equation (2)). The differential effects using different model parameterizations with varying levels of aggregate leverage can be seen in Figure C4 in the appendix. Here, too, $\hat{\beta}_h^{\text{micro}}$ is larger if the initial distribution of firms' leverage is higher.

To test this observation empirically, we estimate a version of our baseline firm-level local projections (2)

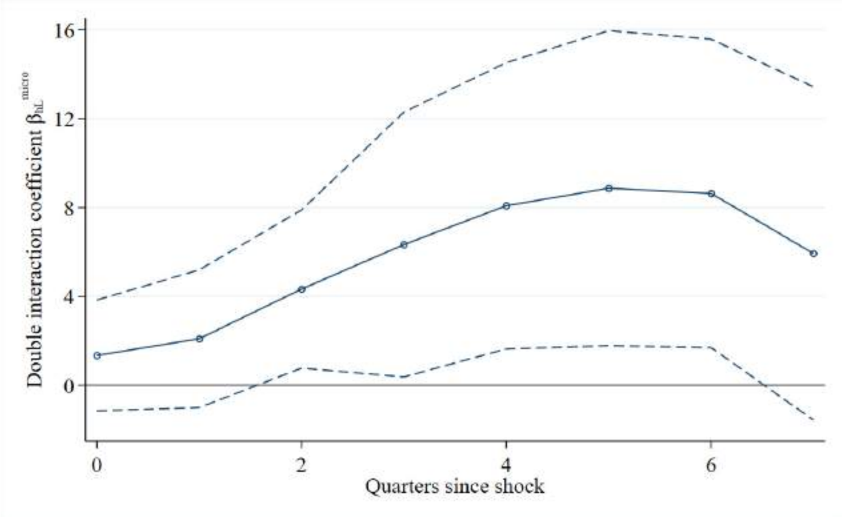
$$\begin{aligned}\log k_{i,t+h} - \log k_{i,t-1} =& \beta_h^{\text{micro}} \tilde{\ell}_{i,t-1} \xi_{ct}^m + \beta_{hL}^{\text{micro}} \tilde{\ell}_{i,t-1} \xi_{ct}^m \tilde{L}_{t-1} + \mathbf{\Gamma'}_h \mathbf{Z}_{i,t-1} \\ &+ \zeta_{ih} + \eta_{sth} + \theta_{cth} + e_{ith},\end{aligned} \tag{8}$$

in which we add an additional term, namely, the interaction of lagged standardized firm leverage, the monetary policy shock, and the lagged standardized aggregate leverage. Given the model, we expect the estimand $\hat{\beta}_{hL}^{\text{micro}}$ to be positive, which implies that a highly leveraged firm's investment response to a monetary policy shock is especially dampened in period of high aggregate leverage.

Figure 10 shows that $\beta_{hL}^{\text{micro}}$ is indeed statistically significantly positive. Given that our baseline effect of financial heterogeneity on the semielasticity of investment is approximately 9pp per standard deviation, the estimated coefficients are also quantitatively meaningful.

Another test of whether differences in the capital price channel can be related to the heterogeneity of firm-level responses to monetary policy relates to the prevalence of used capital goods. Used capital goods tend to display higher business cycle volatility than new ones (Lanteri, 2018, Gavazza and Lanteri, 2021). However, not all firms have access to this capital, as some industries use highly specialized assets for which there is no liquid second-hand market. The firms that do have access pay a lower price for new capital and thus face lower marginal costs of investment after interest rates increase. The capital price channel should be stronger for

Figure 10: State dependence of financial heterogeneity effects of monetary policy



Notes: Estimation of location interaction with a triple interaction, see Equation (8). The coefficients $\hat{\beta}_{hL}^{\text{micro}}$ are depicted. Positive values indicate that the difference in investment responses between high- and low-leverage firms increases if aggregate leverage is high, i.e., if many firms belong to the high-leverage group.

these firms, and because a strong capital price channel mutes the difference between high- and low-leverage firms (as shown in Figure 6), we predict that $\hat{\beta}_{h}^{\text{micro}}$ is lower for firms operating in industries that use a generic capital input used in many other industries. In Table B4 in the appendix, we use the industry-level asset redeployability scores provided by Kim and Kung (2017) to show that this expectation indeed holds, even though the additional interaction term is not statistically significant.

6 Alternative hypotheses

Apart from the general equilibrium explanation proposed in the previous section, we test and reject three hypotheses related to aggregation and selection that might in principle explain the difference between micro and macro elasticities.

6.1 Heterogeneous effects and aggregation (Alternative hypothesis I)

As in most firm data, the firm size distribution in our sample is very heavily skewed: In terms of both assets and employment, the 90th percentile is more than an order of magnitude larger than the median, which itself is an order of magnitude larger than the 10th percentile. In a firm-level analysis, however, each firm receives the same weight. It could be that most firms indeed react less to monetary policy if they have higher leverage, but for a few very large firms, the effect is reversed, so they react more to monetary policy when they have high leverage. Because these large firms are responsible for a large share of aggregate investment, they could potentially overturn the positive coefficient we find for the average firm in Section 3.

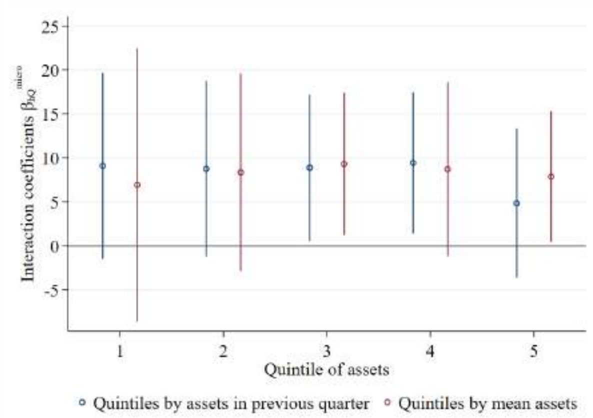
In this subsection, we show that differences in the differential effect by firm size cannot explain the disparity between the firm-level and the aggregate result. We start from Equation (2) and add to the interaction between the monetary policy shock and lagged leverage an additional term $Q_{i,t-1}$, which is the quintile of the firm in the size distribution (defined as total assets) in the quarter before the shock. In an alternative definition, we compute the quintiles based on the firms' average deflated assets, such that Q_i does not vary over time.

$$\log k_{i,t+h} - \log k_{i,t-1} = \beta_{hQ}^{\text{micro}} \left(\frac{\ell_{i,t-1}-\bar{\ell}_i}{\sigma_{\ell,i}}\right) \xi_{ct}^{m} Q_{i,t-1} + \mathbf{\Gamma'}_h \mathbf{Z}_{i,t-1} + \zeta_{ih} + \eta_{sth} + \theta_{cth} + e_{ith} \quad (9)$$

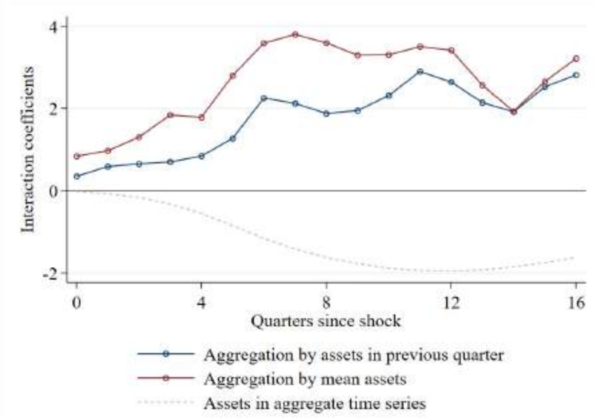
In Figure 11(a) we show the interaction coefficient $\hat{\beta}_{hQ}^{\text{micro}}$ for the sixth quarter ahead for all five groups of firms. The estimate is positive for all five bins. While the 95% confidence intervals we show are relatively wide, most estimates are statistically significantly different from zero at the 10% significance level. The coefficient estimated for the top quintile is somewhat smaller, but it is not statistically significantly different from the other coefficients and is not quantitatively different enough to overturn our firm-level result in the aggregation step.

Figure 11: Heterogeneous effects by firm size

(a) Size quintile interaction for $h = 6$



(b) Aggregated vs. aggregate effect



Notes: The left-hand side plot shows the interaction coefficient $\hat{\beta}_{hQ}^{\text{micro}}$ for $h = 6$ from Equation (9), where $Q_{i,t-1}$ is one of two categorical variables: First, the quintile of firm size (measured as total assets) in the previous quarter; and second, the quintile of the firms' average assets (deflated using the GDP deflator of the respective region). Vertical bars denote the 95% confidence intervals.

We conduct this aggregation more explicitly in Figure 11(b). Specifically, for each observation, we compute the differential effect of monetary policy on capital when leverage varies by 3pp – the standard deviation of leverage in the aggregate data, given the firms' quintile in the size distribution and the estimated, size-specific coefficients.[19] Subsequently, we compute the aggregated capital response as the weighted sum of firm-level response estimates, where the weights are defined as the firm's pre-existing stock of assets. Clearly, the resulting estimate of the aggregated response implied by the firm-level estimates is positive rather than negative;

[19]Notice that larger firms tend to have lower $\sigma_{\ell,i}$ (see Figure A5). Therefore, an equal estimate of $\beta_{hQ}^{\text{micro}}$ implies a larger differential effect per percentage point of leverage for large firms.

we discussed the negative aggregate response in Section 2 and include it in Figure 11(b) for reference.

6.2 Sample selection (Alternative hypothesis II)

The previous alternative hypothesis was based on the idea that very few observations (of the largest firms) nearly disappear in the micro data but actually dominate the aggregate in reality. The opposite could also be true, namely that many, potentially very differently behaving firms are not selected into the micro data, but due to their large mass, dominate aggregate fluctuations. Caglio et al. (2022) argue along these lines, suggesting that the estimated interaction coefficient $\hat{\beta}_h^{\text{micro}}$ might be positive for a sample of large firms only. Indeed, in their sample of small- and medium-sized enterprises, the estimate of the interaction coefficient between leverage and monetary policy is significantly negative (but small).[20] At the same time, the bottom 99% of the firm size distribution accounts for less than 20% of aggregate investment and assets (Crouzet and Mehrotra, 2020).

The firms in our regression sample together hold around a fourth of the aggregate capital stock, measured by the sum of fixed assets relative to the stock of nonfinancial assets in the nonfinancial business sector (see Figure A1(b) in the appendix). We argue that the remaining three quarters are unlikely to alter the results to a degree that they can turn a positive $\hat{\beta}_h^{\text{micro}}$ into a negative one when aggregated. To see why, let g_t^K and g_t^S be the growth rates of the aggregate capital stock K_t and the aggregated capital stock owned by all firms in our sample, defined as $S_t = \sum_{i \in S} k_{i,t}$, respectively. For simplicity, we assume a constant $\alpha = S_t/K_t = 0.25$. g_t^K can be approximated by

$$g_t^K = \alpha g_t^S + (1-\alpha)\tilde{g}_t, \tag{10}$$

where $\tilde{g}$ is the growth rate of the aggregated capital stock of all firms that are not in our sample. For g^S to be 2% when g^K is -1% – which are the approximate magnitudes of the medium-term responses of capital shown in Figure 11(b) –, $\tilde{g}$ must be -2%. For realizations of g_t^K, g_t^S, and (unobserved) $\tilde{g}_t$ that are consistent with these impulse response functions, a regression of $\tilde{g}_t$ on g_t^S must therefore estimate a coefficient $\hat{\beta}^{\tilde{g},g^S} = \text{Cov}(g_t^S, \tilde{g}_t)/\text{Var}(g_t^S) = -1$.

Taking variances on both sides of Equation (10), we obtain

$$\text{Var}(g_t^K) = \alpha^2 \text{Var}(g_t^S) + (1-\alpha)^2 \text{Var}(\tilde{g}_t) + 2\alpha(1-\alpha)\text{Cov}(g_t^S, \tilde{g}_t). \tag{11}$$

The variance in the quarterly growth rates of aggregate capital ($\text{Var}(g_t^K)$) on the left-hand side is 3.83 over the relevant sample. When we compute S_t based on our sample, the variance of

[20] A crucial difference between their and our estimation, however, is that they define high-leverage firms in a time-invariant way, whereas we exploit only within-firm variation in leverage to exclude the possibility that there are permanent unobserved heterogeneities across firms' response to monetary policy.

its quarterly growth rate ($\text{Var}(g_t^S)$) is 6.26.[21] These values are shown in the first two columns of Table 2. Given the above restriction between $\text{Cov}(g_t^S, \tilde{g}_t)$ and $-\text{Var}(g_t^S)$, we can identify the variance of $\tilde{g}_t$ that is consistent with these observables, shown in the third column. Specifically, it is greater than 10, which is implausibly volatile. Crouzet and Mehrotra (2020) show that the *aggregated* stock of small firms – which are presumably not the ones included in our micro data – is not more sensitive to the business cycle than the stock of large firms.

Table 2: Variances of quarterly capital stock growth rates: Aggregate and aggregated

	Aggregate capital	Aggregated capital from micro data		Resulting comovement	
Assumption:	$\text{Var}(g_t^K)$	$\text{Var}(g_t^S)$	$\text{Var}(\tilde{g}_t)$	$\text{Cov}(g_t^S, \tilde{g}_t)$	$\hat{\beta}^{\tilde{g},g^S}$
$\text{Var}(\tilde{g}_t)$ needed for $\hat{\beta}^{\tilde{g},g^S} = -1$	3.83	6.26	10.29	-6.26	-1.00
Realistic values	3.83	6.26	7.13	-1.53	-0.24

Notes: The first two columns show the variances in the growth rate of the aggregate capital stock K_t as well as the aggregated stock of our sample firms S_t. To compute the latter, we compute chain-linked values to account for the sample changes over time. The other three rows show the volatility of aggregated capital stock growth of all firms from our sample and its covariance with observed variables as implied by Equations (10) and (11).

The second row assumes a more realistic variance of $\tilde{g}_t$ of approximately 7, given the data. This value reflects the variance in quarterly growth rates of $K_t - S_t$, which we use to approximate the volatility of the aggregated stock of capital of all firms not in our sample. Given this assumption, Equation (11) implies that the comovement between $\tilde{g}_t$ and g_t^S is still negative but substantially less so. A less negative comovement between the aggregated capital stocks of sample and non-sample firms, however, means that the implied response of the non-sample firms is not strong enough to overturn the response of the sample firms.

Overall, the firms not covered in our sample might behave differently than the firms we observe, both unconditionally and conditional on monetary policy shocks. This has the potential to reduce the aggregate implications of the estimated micro elasticity of investment to monetary policy by leverage. However, given realistic values for the cyclicality of non-sample firms, they will not be able to turn the positive micro estimates into negative values at the aggregate level.

6.3 Endogenous exit (Alternative hypothesis III)

Another form of sample selection could arise endogenously in response to the monetary policy shock. In the micro data, we observe only the responses of firms that continue operating. This feature is not an issue with the macro data, which accounts for the fact that capital by exiting firms can be bought by other firms. Could this, however, be a source of bias that could account for the difference between our micro- and macro-based elasticities? We argue that this is not the case.

[21] We use nominal values to compute variances in both the aggregate and the aggregated capital stock based on sample firms because it is the variable that is most directly comparable between micro and macro data. In the micro data, we observe the end-of-quarter balance of capital whereas in the aggregate data, the financial accounts for the US report the total of the end-of-quarter balance of capital in the nonfinancial business sector.

In our firm-level local projections, we have modeled changes in a firm's capital as a function of monetary policy shocks, the firm's preexisting leverage and their interaction, among other elements (see Equation (2)), that is, $\Delta \log k_i = \mathbf{X_i}'\beta^I$ when all covariates are collected in the vector $\mathbf{X_i}$. β^I are the linear coefficients, and the superscript I indicates that they estimate only the intensive margin of capital adjustment. The familiar OLS estimator for the relationship between $\Delta \log k_i$ and $\mathbf{X_i}$ is

$$\hat{\beta}^I = \frac{Cov(\Delta \log k_i, \mathbf{X_i})}{Var(\mathbf{X_i}, \mathbf{X_i})}. \tag{12}$$

If we stipulate instead that the "true" latent data-generating process follows $\Delta \log k_i = \Phi(\mathbf{X_i}'\beta^* < c)\, \mathbf{X_i}'\beta^*$; i.e., it includes an extensive margin where we observe $\mathbf{X_i}'\beta^*$ with some probability and zero otherwise (e.g. if the resulting change in capital is below the preexisting capital stock), where Φ is the normal cumulative distribution. The respective estimator can be expressed as

$$\hat{\beta}^* = \frac{1}{\Phi(\mathbf{X_i}'\beta^* < c)} \frac{Cov(\Delta \log k_i, \mathbf{X_i})}{Var(\mathbf{X_i}, \mathbf{X_i})}. \tag{13}$$

Given that Φ is bound between 0 and 1, it is possible that the estimator (12) underestimates (in absolute values) the true effect $\hat{\beta}^*$, but it is not possible for the two estimators to have a different sign. Therefore, the endogenous exit of some firms cannot explain the fact that we estimate $\hat{\beta}_h^{\text{micro}} > 0$ in the firm data but $\hat{\beta}_h^{\text{macro}} < 0$ in aggregate time series.

7 Conclusions

In this paper, we show that the real effects of monetary policy through the investment channel is stronger when corporate leverage is high. We refer to this observation as the macro elasticity. It stands in sharp contrast to firm-level results, where we find – in line with Ottonello and Winberry (2020) – that leverage dampens the response of investment. The common interpretation of what we refer to as the micro elasticity is that risky, high-leverage firms face higher costs of investment due to additional risk premia, which increase disproportionately with leverage. Thus, high-leverage firms operate on a steeper part of the marginal cost curve. When policymakers change the policy rate, the shift in the marginal benefit curve is therefore muted for these firms.

We have explored several possibilities that might reconcile the difference in sign between micro and macro elasticities. Our preferred explanation takes the above interpretation as given but acknowledges general equilibrium effects. Through the relative price of capital, the distribution of leverage among *all* firms affects the response of each individual firm. When most firms are highly leveraged and – as implied by the micro elasticity – reduce demand for investment relatively little in response to monetary policy, the decrease in the relative price of capital is small. Because the capital price stays high, the average firm strongly reduces investment and aggregate investment contracts.

This state dependence of aggregate monetary policy effects is of first-order importance to policymakers. Aggregate leverage, which is modestly countercyclical, relatively slow-moving and known practically in real-time, significantly amplifies the investment channel of interest rate changes. Our results help to project the likely effects of their policy options on corporate investment, the most volatile component of aggregate demand, more accurately.

References

Alder, Marie, Nuno Coimbra, and Urszula Szczerbowicz, "Corporate debt structure and heterogeneous monetary policy transmission," *Banque de France Working Paper*, 2023, *933.*

Alpanda, Sami, Eleonora Granziera, and Sarah Zubairy, "State dependence of monetary policy across business, credit and interest rate cycles," *European Economic Review*, 2021, *140*, 103936.

Anderson, Gareth and Ambrogio Cesa-Bianchi, "Crossing the credit channel: credit spreads and firm heterogeneity," *American Economic Journal: Macroeconomics*, 2024, *16* (3), 417–446.

Ascari, Guido and Timo Haber, "Non-linearities, state-dependent prices and the transmission mechanism of monetary policy," *The Economic Journal*, 2022, *132* (641), 37–57.

Auer, Simone, Marco Bernardini, and Martina Cecioni, "Corporate leverage and monetary policy effectiveness in the euro area," *European Economic Review*, 2021, *140*, 103943.

Bahaj, Saleem, Angus Foulis, Gabor Pinter, and Paolo Surico, "Employment and the residential collateral channel of monetary policy," *Journal of Monetary Economics*, 2022, *131*, 26–44.

Balli, Hatice Ozer and Bent E. Sørensen, "Interaction effects in econometrics," *Empirical Economics*, 2013, *45* (1), 583–603.

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist, "The financial accelerator in a quantitative business cycle framework," in "Handbook of Macroeconomics, Volume 1, Part C," Elsevier, 1999, chapter 21, pp. 1341–1393.

Bianchi, Javier, "Overborrowing and systemic externalities in the business cycle," *American Economic Review*, 2011, *101* (7), 3400–3426.

Bruns, Martin and Michele Piffer, "A new approach to smooth transition vector autoregressions," *The Econometrics Journal*, forthcoming.

Caggiano, Giovanni, Efrem Castelnuovo, and Giovanni Pellegrino, "Estimating the real effects of uncertainty shocks at the zero lower bound," *European Economic Review*, 2017, *100*, 257–272.

Caglio, Cecilia, R. Matthew Darst, and Şebnem Kalemli-Özcan, "Collateral heterogeneity and monetary policy transmission: Evidence from loans to SMEs and large firms," *NBER Working Paper*, 2022, *28685.*

Cao, Jin, Torje Hegna, Martin B. Holm, Ragnar Juelsrud, Tobias König, and Mikkel Riiser, "The investment channel of monetary policy: Evidence from Norway," *Norges Bank Working Paper*, 2023.

Castelnuovo, Efrem and Giovanni Pellegrino, "Uncertainty-dependent effects of monetary policy shocks: A new-Keynesian interpretation," *Journal of Economic Dynamics and Control*, 2018, *93*, 277–296.

Chetty, Raj, John N. Friedman, Tore Olsen, and Luigi Pistaferri, "Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from Danish tax records," *The Quarterly Journal of Economics*, 2011, *126* (2), 749–804.

Cloyne, James, Clodomiro Ferreira, and Paolo Surico, "Monetary policy when households have debt: New evidence on the transmission mechanism," *The Review of Economic Studies*, 2020, *87* (1), 102–129.

_ , _ , Maren Froemel, and Paolo Surico, "Monetary policy, corporate finance, and investment," *Journal of the European Economic Association*, 2023, *21* (6), 2586–2634.

Coimbra, Nuno and Hélène Rey, "Financial cycles with heterogeneous intermediaries," *Review of Economic Studies Limited*, 2024, *91*, 817–857.

Covas, Francisco and Wouter J. Den Haan, "The Cyclical Behavior of Debt and Equity Finance," *American Economic Review*, 2011, *101*, 877.899.

Crouzet, Nicolas, "Aggregate implications of corporate debt choices," *Review of Economic Studies*, 2018, *85*, 1635–1682.

_ and Neil R. Mehrotra, "Small and large firms over the business cycle," *American Economic Review*, 2020, *110* (11), 3549–3601.

Cummins, Jason G. and Giovanni L. Violante, "Investment-specific technical change in the United States (1947–2000): Measurement and macroeconomic consequences," *Review of Economic Dynamics*, 2002, *5* (2), 243–284.

DiCecio, Riccardo, "Sticky wages and sectoral labor comovement," *Journal of Economic Dynamics and Control*, 2009, *33* (3), 538–553.

Durante, Elena, Annalisa Ferrando, and Philip Vermeulen, "Monetary policy, investment and firm heterogeneity," *European Economic Review*, 2022, *148*, 104251.

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong, "State-dependent effects of monetary policy: The refinancing channel," *American Economic Review*, 2022, *112* (3), 721–61.

Ferreira, Thiago R.T., Daniel A. Ostry, and John Rogers, "Firm financial conditions and the transmission of monetary policy," *Finance and Economics Discussion Series*, 2023, *2023-037.*

Flodén, Martin, Matilda Kilström, Jósef Sigurdsson, and Roine Vestman, "Household debt and monetary policy: Revealing the cash-flow channel," *The Economic Journal*, 2020, *131* (636), 1742–1771.

Gabaix, Xavier, "The granular origins of aggregate fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

Gavazza, Alessandro and Andrea Lanteri, "Credit shocks and equilibrium dynamics in consumer durable goods markets," *Review of Economic Studies*, 2021, *88*, 2935–2969.

Gertler, Mark and Peter Karadi, "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

_ and Simon Gilchrist, "Monetary policy, business cycles, and the behavior of small manufacturing firms," *The Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Gilchrist, Simon and Benoit Mojon, "Credit risk in the euro area," *The Economic Journal*, 2018, *128* (608), 118–158.

_ and Egon Zakrajšek, "Credit spreads and business cycle fluctuations," *American Economic Review*, 2012, *102* (4), 1692–1720.

Giroud, Xavier and Holger M. Mueller, "Firm leverage, consumer demand, and employment losses during the Great Recession," *The Quarterly Journal of Economics*, 2017, *132* (1), 271–316.

Gnewuch, Matthias and Donghai Zhang, "Monetary policy, firm heterogeneity, and the distribution of investment rates," 2022.

Goodhart, Charles A.E., M. Udara Peiris, Dimitrios Tsomocos, and Xuan Wang, "Corporate legacy debt, inflation, and the efficacy of monetary policy," 2022.

Graham, John R and Mark T Leary, "A review of empirical capital structure research and directions for the future," *Annu. Rev. Financ. Econ.*, 2011, *3* (1), 309–345.

Hazell, Jonathan, Juan Herre no, Emi Nakamura, and Jón Steinsson, "The slope of the Phillips Curve: Evidence from U.S. States," *Quarterly Journal of Economics*, 2022, *137* (3), 1299–1344.

Holm-Hadulla, Fédéric and Claire Thürwächter, "Granular shocks to corporate leverage and the macroeconomic transmission of monetary policy," *Banque de France Working Paper*, 2023, *933.*

Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek, "The transmission of monetary policy under the microscope," *Journal of Political Economy*, 2021, *129* (10), 2861–2904.

Iwata, Shigeru and Shu Wu, "Estimating monetary policy effects when interest rates are close to zero," *Journal of Monetary Economics*, 2006, *53* (7), 1395–1408.

Jarociński, Marek and Peter Karadi, "Deconstructing monetary policy surprises – the role of information shocks," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 1–43.

Jeenas, Priit, "Firm balance sheet liquidity, monetary policy shocks, and investment dynamics," 2024.

Jermann, Urban and Vincenzo Quadrini, "Macroeconomic effects of financial shocks," *American Economic Review*, 2012, *102* (1), 238–271.

Jungherr, Joachim, Matthias Meier, Timo Reinelt, and Immo Schott, "Corporate debt maturity matters for monetary policy," *Working Paper*, 2022.

Khan, Aubhik and Julia Thomas, "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 2008, *76* (2), 395–436.

Kim, Hyunseob and Howard Kung, "The asset redeployability channel: How uncertainty affects corporate investment," *Review of Financial Studies*, 2017, *30* (1), 245–280.

Kiyotaki, Nobuhiro and John Moore, "Credit cycles," *Journal of Political Economy*, 1997, *105* (2), 211–248.

Koby, Yann and Christian K. Wolf, "Aggregation in heterogeneous-firm models: Theory and measurement," *mimeo*, 2020.

Koop, Gary, M. Hashem Pesearan, and Simon M. Potter, "Impulse response analysis in nonlinear multivariate models," *Journal of Econometrics*, 1996, *74* (1), 119–147.

Lakdawala, Aeimit and Timothy Moreland, "Monetary policy and firm heterogeneity: The role of leverage since the financial crisis," *Available at SSRN 3405420*, 2021.

_ **and** _ , "Firm-level uncertainty and the transmission of monetary policy," *Review of Economics and Statistics*, forthcoming.

Lanteri, Andrea, "The market for used capital: Endogenous irreversibility and reallocation over the business cycle," *American Economic Review*, 2018, *108* (9), 2383–2419.

Lhuissier, Stéphane and Urszula Szczerbowicz, "Monetary policy and corporate debt structure," *Oxford Bulletin of Economics and Statistics*, 2022, *84* (3), 497–515.

Li, Dake, Mikkel Plagborg-Møller, and Christian K. Wolf, "Local projections vs. VARs: Lessons from thousands of DGPs," *NBER Working Paper Series*, 2022, *30207.*

Lian, Chen and Yueran Ma, "Anatomy of corporate borrowing constraints," *The Quarterly Journal of Economics*, 2021, *136* (1), 229–291.

Lorenzoni, Guido, "Inefficient credit booms," *The Review of Economic Studies*, 2008, *75* (3), 809–833.

Orchard, Jacob, Valerie A. Ramey, and Johannes F. Wieland, "Micro MPCs and macro counterfactuals: The case of the 2008 rebates," *NBER Working Paper*, 2023, *31584.*

Ottonello, Pablo and Thomas Winberry, "Financial heterogeneity and the investment channel of monetary policy," *Econometrica*, 2020, *88* (6), 2473–2502.

Pellegrino, Giovanni, Federico Ravenna, and Gabriel Züllig, "The impact of pessimistic expectations on the effects of COVID-19-induced uncertainty in the euro area," *Oxford Bulletin of Economics and Statistics*, 2021, *83* (4), 841–869.

Rogerson, Richard and Johanna Wallenius, "Micro and macro elasticities in a life cycle model with taxes," *Journal of Economic Theory*, 2009, *144*, 2277–2292.

Romer, Christina D. and David H. Romer, "A new measure of monetary shocks: Derivation and implications," *American Economic Review*, 2004, *94* (4), 1055–1084.

Tenreyro, Silvana and Gregory Thwaites, "Pushing on a string: US monetary policy is less powerful in recessions," *American Economic Journal: Macroeconomics*, 2016, *8* (4), 43–74.

Vats, Nishant, "Financial constraints and the transmission of monetary policy: Evidence from relaxation of collateral constraints," *mimeo*, 2023.

Wieland, Johannes and Mu-Jeung Yang, "Financial dampening," *Journal of Money, Credit and Banking*, 2020, *52* (1), 79–113.

Winberry, Thomas, "Lumpy investment, business cycles, and stimulus policy," *American Economic Review*, 2021, *111* (1), 364–96.

Wu, C.F.J., "Jackknife, bootstrap and other resampling methods in regression analysis," *Annals of Statistics*, 1986, *14* (1), 1261–1350.

Appendices

A Data description and verification

A.1 Data sources for aggregate time series

Table A1: Main aggregate time series and data sources

Variable	Definition	Retrieved from	Original source	Transform.
Dependent variables				
Investment	Real gross private domestic investment, chained 2012 dollars	FRED: GPDIC1	BEA	$100 \times \log$
Assets	Nonfin. assets at historical costs	FRED: TABSNNCB	Fed. Res. Board	$100 \times \log$
Shock variables				
Fed Funds rate	Effective Federal Funds rate (end of period)	FRED: FEDFUNDS	Fed. Res. Board	Δ
ξ_t^m	High-frequency announcement surprises	Jarociński and Karadi (2020)		
Leverage				
Liabilities NFB	Total liabilities of nonfinancial corporate businesses	FRED TLBSNNCB	Fed. Res. Board	
Assets NFB	Total assets of nonfinancial corporate businesses	FRED TABSNNCB	Fed. Res. Board	
Leverage (L)	Aggregate corporate leverage	Own calculations		$100\,\frac{\text{Liab. NFB}}{\text{Ass. NFB}}$
Control variables				
GDP	Real gross domestic product in chained 2012 dollars	FRED: GDPC1	BEA	$\Delta 100 \times \log$
CPI	Consumer price index, all items in US city average	FRED: CPIAUCSL	BLS	$\Delta 100 \times \log$
Core CPI	—, all items less food and energy in US city average	FRED: CPILFESL	BLS	$\Delta 100 \times \log$
PPI	Producer price index, all commodities	FRED: PPIACO	BLS	$\Delta 100 \times \log$
Price defl. inv.	Implicit price deflator of gross domestic private investment	FRED A006RD3Q086SBEA	BEA	$\Delta 100 \times \log$
Bond spread	Corporate bond yields rel. to risk-free asset of same maturity	Gilchrist and Zakrajšek (2012)		

Notes: Values of higher-than-quarterly frequency variables are averaged within the quarter, with the exception of the federal funds rate, for which we use end-of-quarter values.

Table A2: Auxiliary aggregate time series and data sources (part 1)

Variable	Definition	Retrieved from	Original source	Transformation
Alternative liability measures				
Debt securities	Debt securities of nonfinancial corporate businesses	FRED: NCBDBIQ027S	Fed. Res. Board	
Loans and mortgages	Loans and mortgages of nonfinancial corporate businesses	FRED: NCBLL	Fed. Res. Board	
Debt	Sum of Debt securities and Loans and mortgages	Own calculation		$100 \frac{\text{Debt}}{\text{Ass. NFB}}$
C&I loans	Commercial and industrial loans of all commercial banks	FRED: BUSLOANS	Fed. Res. Board	—
Short-term	Total short-term liabilities of nonfinancial corporate businesses	FRED: BOGZ1FL104150005Q	Fed. Res. Board	—
Other variables related to investment and capital				
As real components of non-residential investment are not available for the full time series, we calculate them ourselves by dividing nominal variables by implicit price deflators:				
Nominal investment	Nominal gross private domestic investment at current prices: Structures, Equipment, Intellectual property products	FRED: B009RC1Q027SBEA, Y033RC1Q027SBEA, Y001RC1Q027SBEA	BEA	
Investment price	Implicit price defl. of investment: Structures, Equipment, Intellectual property products	FRED: A009RD3Q086SBEA, Y033RD3Q086SBEA, Y001RD3Q086SBEA	BEA	$100 \times \log$
GDP defl.	GDP implicit price deflator	FRED: USAGDPDEFQISMEI	OECD	
Rel. price o. investment	Ratio between Price defl. inv. and GDP defl.	Own calculation		$100 \times \log$
Rel. price o. inv. goods	Relative price of investment goods	FRED: PIRIC	DiCecio (2009)	$100 \times \log$
Rel. price o. equipment	Relative price of equipment	FRED: PERIC	DiCecio (2009)	$100 \times \log$
N-f. assets at hist. cost	Non-financial assets at historical cost, measure of real capital stock	FRED: TTAATASHCBSHNNCB	Fed. Res. Board	$100 \times \log$

Notes: Macro variables used throughout Section 2 and appendices in addition to Table A1. Quarterly averages of higher-frequency variables.

Table A3: Auxiliary aggregate time series and data sources (part 2)

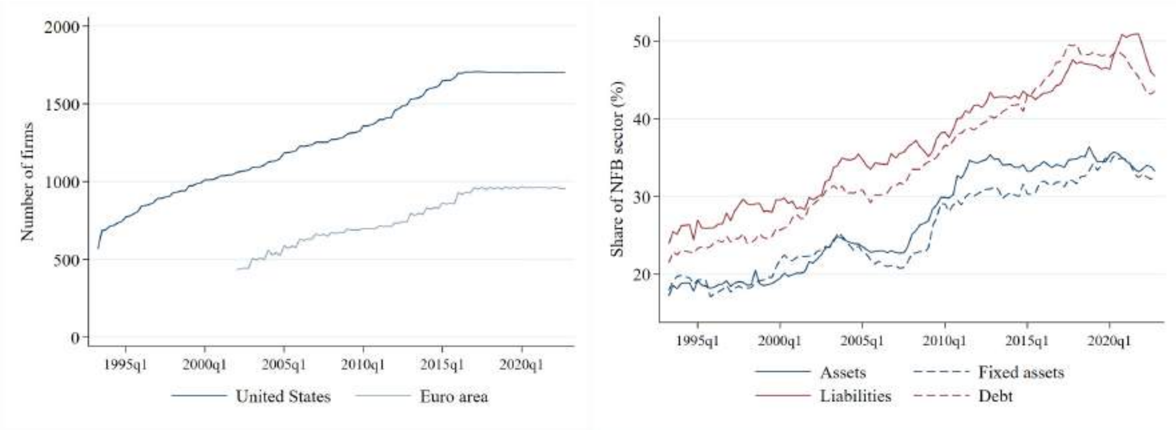
Variable	Definition	Retrieved from	Original source	Transformation
Other variables				
Long-term government bond yield	Market yield on US Treasury securities at 10-year const. matur.	FRED: DGS10	Fed. Res. Board	
Excess bond premium	Corporate bond spread not explained by default risk	Gilchrist and Zakrajšek (2012)		
Output gap	Percent deviation of GDP from real potential gross domestic product in chained 2012 dollars	FRED: GDPPOT	CBO	
Mortgage LTV ratio	Ratio of i.) real estate loans and ii.) value of owner-occupied real estate owned by households	FRED: RELACBW-027SBOG, FRED: HOOREVLMHMV	Fed. Res. Board	
Consumer loans	Ratio of i.) consumer loans and ii.) nominal GDP (= real GDP $\times$ GDP defl.)	FRED: CLSACBW027SBOG	Fed. Res. Board, BEA	
Liquidity ratio	Ratio of liquid to total assets	FRED: BOGZ1FL104001005Q	Fed. Res. Board	
Profitability	Profit per unit of real gross value added	FRED: A466RD3Q052SBEA	BEA	
R&R shocks	Romer and Romer (2004)-type shocks extended until 2007	Wieland and Yang (2020)		

Notes: Macro variables used throughout Section 2 and appendices in addition to Tables A1 and A2. Quarterly averages of higher-frequency variables.

A.2 Firm balance sheets

Figure A1: Sample size

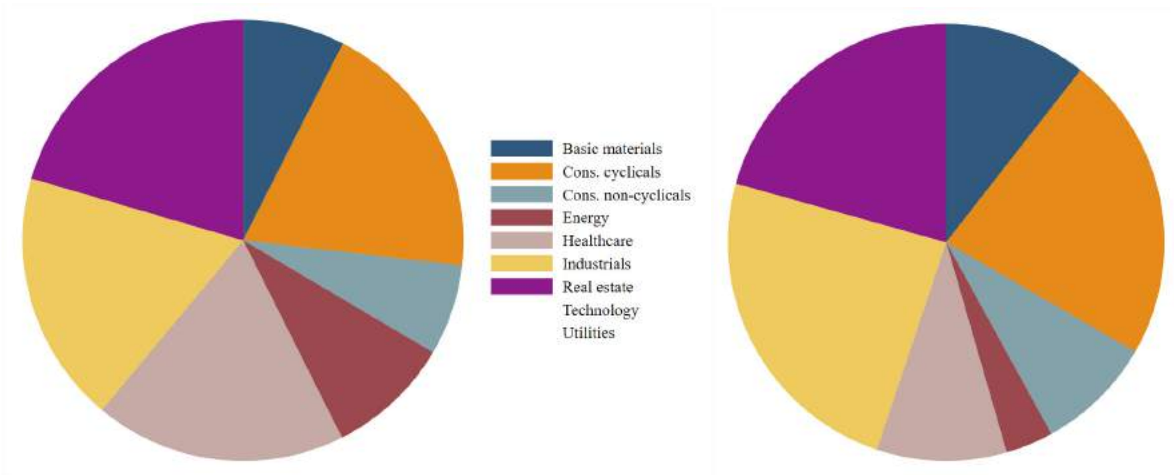
(a) Number of firms in sample (b) US: Aggregated balance sheets



Notes: Left-hand side: Number of firms in the sample, which is described in Section 3.2. Right-hand side: For the US, we sum all assets, fixed assets (=capital), liabilities, and debt (as a subcategory of liabilities), respectively, of the firms in a sample for each quarter and compute the ratio between this aggregated sum and the aggregate equivalent published in the US financial accounts (see Table A1). Reading example: At the end of the sample, the ca. 1,800 US firms' assets cover approximately 35% of all assets of nonfinancial businesses in the US and approximately 50% of their liabilities. The reasons why the share of liabilities covered by our data is higher than the share of assets are that larger firms are more highly leveraged (see Figure A5) and our firms are substantially larger than the average US firm.

Figure A2: Distribution of broad economic sectors by sample

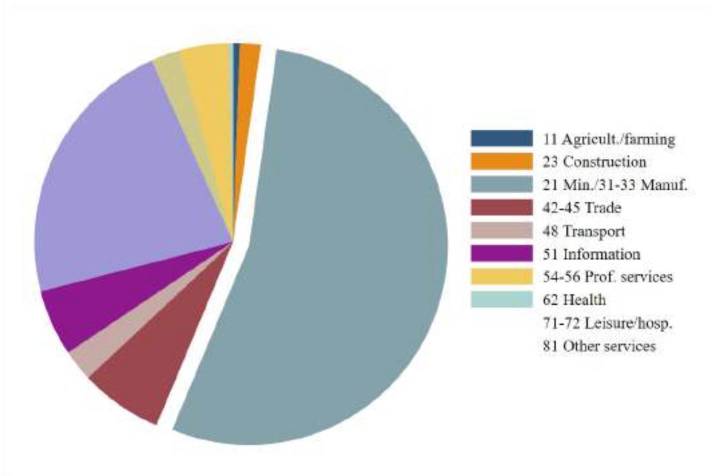
(a) US (b) Euro area



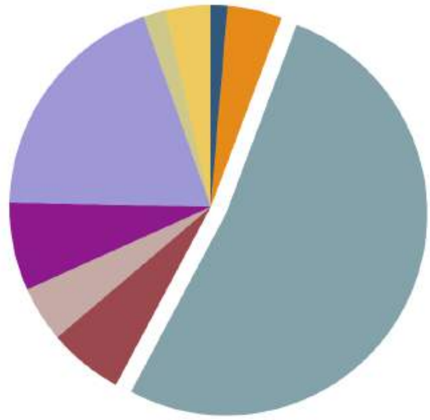
Notes: Allocation of the sample firms into 9 broad economic sectors defined by the data provider (LSEG). The sample excludes the real estate and utilities sectors, as in Ottonello and Winberry (2020). See Section 3.2 for further details on the data.

Figure A3: Distribution of NAICS industries by sample

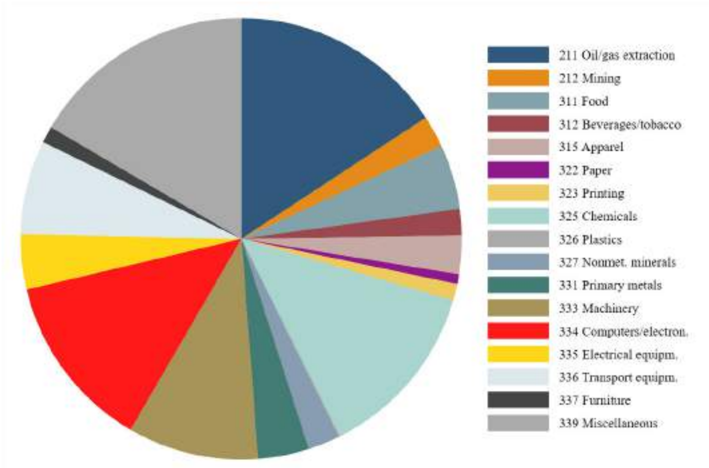
(a) US



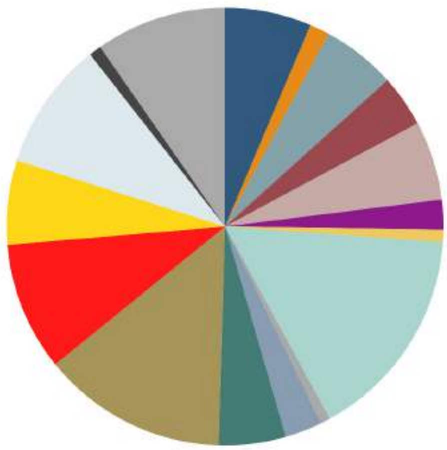
(b) Euro area



(c) US, manufacturing firms only

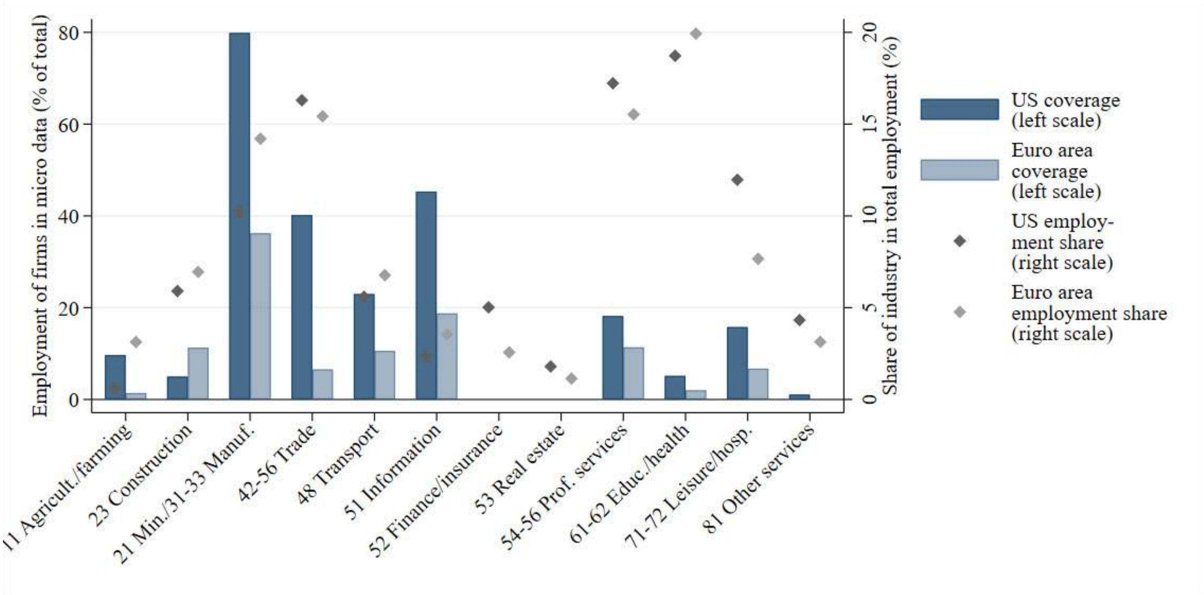


(d) Euro area, manufacturing firms only



Notes: Allocation of the sample firms according to 2- and 3-digit NAICS codes. The data provider lists subsectors to the sectors shown in Figure A2, which we manually match to the best-fitting NAICS sector. See Section 3.2 for further details on the data.

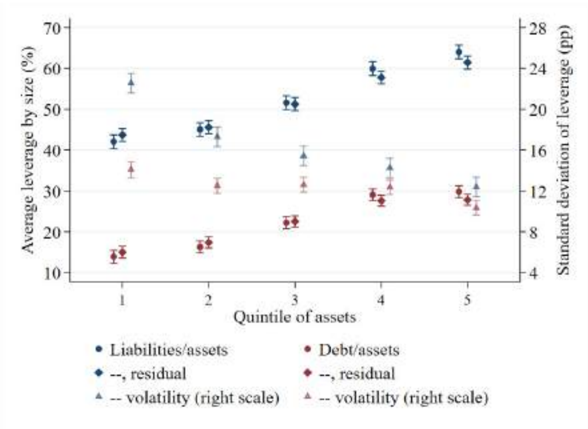
Figure A4: Employment by industry



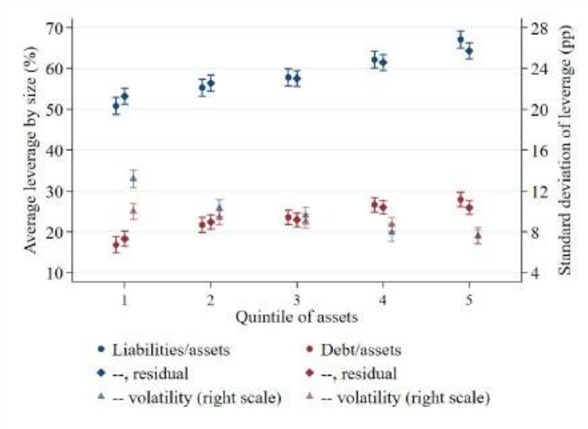
Notes: In our sample of ca. 2,800 firms, we observe employment only for slightly over 90% of firms. To assess the coverage of our firm-level data, we compare the sum of full-time equivalents of all available firms in 2022 to nonfarm payrolls by NAICS industries (for the US) and employment by NACE (for the euro area). The latter have been translated into NAICS codes beforehand and some industries have been slightly aggregated further from the 2-digit level. The grey diamonds denote the share of industry-level employment in total employment, bars denote the sum of private-sector employment of firms in our sample relative to total employment in the sector according to the national accounts. The firms in our sample represent a sizeable share of overall private-sector employment. Generally, the coverage is higher in industries where there are fewer and larger firms (see, e.g. mining/manufacturing), whereas it is below 20% in industries typically characterized by many small and/or privately owned firms. Coverage in finance/insurance and real estate is 0 because these firms are excluded from the sample. The coverage is an approximation, and several caveats apply: Along with missing values for 10% of firms, all employment is fully assigned to the home country of a firm in the micro data, whereas it is based on establishment location in the national accounts.

Figure A5: Leverage by firm size

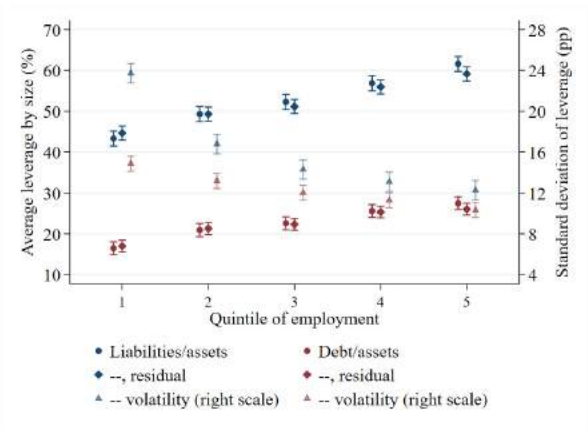
(a) US by assets



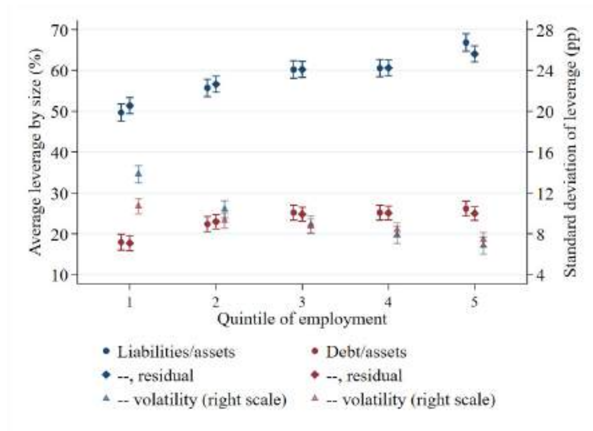
(b) Euro area by assets



(c) US by employment



(d) Euro area by employment



Notes: We compute the following measures at the firm level: i.) average leverage $\bar{\ell}_i$ over the time period the firm is measured either by the ratio of liabilities to assets (our baseline measure, in blue) or debt to assets (in red), ii.) the within-firm standard deviation of leverage, and iii.) corrected measures of average leverage. To compute this correction, we first take the panel and regress leverage on a NAICS industry and a time fixed effect for both regions separately. We add to the residual the average leverage of all firms. Additionally, iv.), we deflate assets in the panel of balance sheets by the GDP deflator of the respective region, compute the firm mean of that real asset measure and assign each firm to the respective quintile. We then regress measures i.) to iii.) on iv.) and show the coefficients in the two top panels, along with 95% confidence intervals. The bottom panels show equivalent estimates when regressed on employment quintiles, which we observe for 90% of firms.

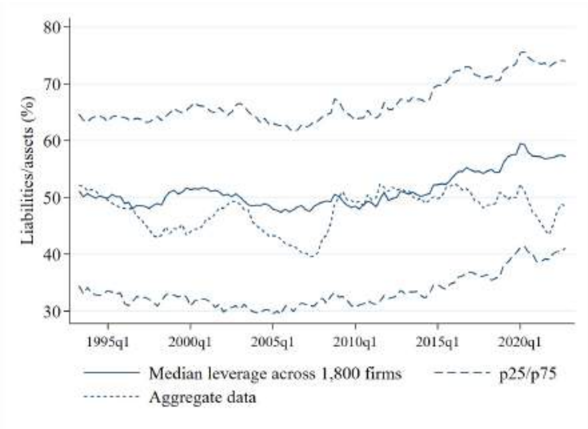
Table A4: Descriptive statistics

Variable	Obs.	Mean	p10	p25	p50	p75	p90
United States							
Sales (mn 2015 USD)	150,812	895.95	7.55	49.72	223.48	856.17	2,997.04
Real sales growth	147,214	3.07	-17.08	-5.32	1.78	9.82	24.82
Fix. ass. (mn 2015 USD)	150,887	1,978.56	11.21	60.52	322.75	1,545.20	6,442.75
Fixed asset growth (%)	148,644	1.90	-6.26	-2.56	-0.14	3.65	13.43
Liabilities/assets (%)	151,089	51.75	18.78	33.87	51.94	67.84	84.51
—, firm average	1,831	52.53	27.50	39.20	52.64	65.77	77.67
—, avg. 1993-2007	1,261	49.17	22.58	33.83	49.01	63.07	74.97
—, avg. 2008-19	1,826	53.55	26.85	39.48	53.57	67.37	80.31
—, standard dev. (pp)	1,831	16.38	6.33	8.96	13.25	21.16	34.21
Debt/assets (%)	139,718	22.09	0.00	3.99	20.10	35.04	50.81
—, firm average	1,669	23.45	3.26	10.77	21.95	33.97	48.96
—, standard dev. (pp)	1,669	12.32	4.56	7.34	10.67	15.80	24.95
Short-t. liab./assets (%)	151,067	22.58	8.05	12.72	19.80	29.44	41.40
EBIT (% of sales)	148,247	3.56	-19.77	2.02	7.95	14.94	24.31
Current ass. (% of total)	151,080	47.81	15.53	29.33	46.64	65.73	81,16
Employment (FTE)	1,690	12,906.30	225	910	3,555	12,850	37,000
Euro area							
Sales (mn 2015 EUR)	62,024	752.61	11.67	35.44	134.02	603.44	2,485.62
Real sales growth (%)	61,071	2.22	-13.61	-2.55	-0.30	6.77	20.64
Fix. ass. (mn 2015 EUR)	62,546	1,803.28	11.87	48.99	234.04	1,307.78	5,719.23
Fixed asset growth (%)	60,831	1.48	-4.84	-1.31	-0.36	2.21	9.84
Liabilities/assets (%)	62,585	58.53	32.56	46.65	59.57	71.74	81.86
—, firm average	1,050	58.61	35.32	47.97	59.99	70.01	79.36
—, avg. 1993-2007	692	59.25	35.71	47.42	60.72	72.10	80.19
—, avg. 2008-19	1,048	58.48	34.44	47.61	59.29	70.66	79.84
—, standard dev. (pp)	1,050	9.72	4.04	5.34	7.81	11.68	17.60
Debt/assets (%)	57,054	23.33	1.83	10.55	22.30	34.09	45.43
—, firm average	950	23.82	6.71	13.08	22.58	32.83	43.36
—, standard dev. (pp)	947	8.88	3.64	5.35	7.75	11.04	15.40
Short-t. liab./assets (%)	62,440	32.10	14.57	21.67	30.79	42.24	54.33
EBIT (% of sales)	61,734	5.31	-4.47	2.51	6.74	12.33	20.02
Current ass. (% of total)	62,570	49.13	22.08	34.34	49.03	63.61	76.49
Employment (FTE)	961	12,541	255	773	2,568	10,444	36,506

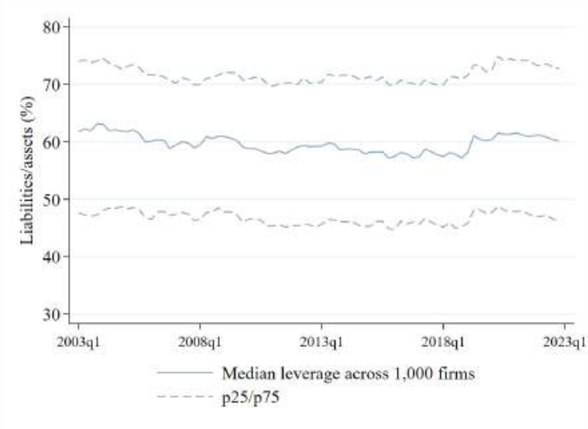
Notes: Moments of leverage and other firm characteristics for firm-years as well as at the firm level. The first four rows in each panel use the GDP deflator of the respective region to deflate nominal variables. Total assets contain the sum of total net property, plant & equipment, net intangibles, long term investments, other total long-term assets, other total assets, and total net utility plant for the fiscal period. Employment is available only for ca. 90% of firms. To compute the means, the data were winsorized at the 5th and 95th percentiles.

Figure A6: Leverage over time

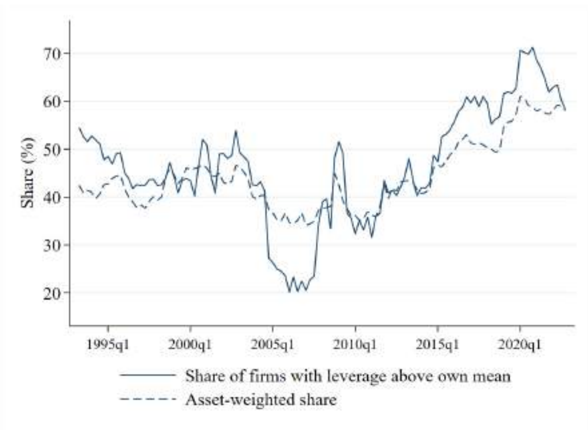
(a) United States



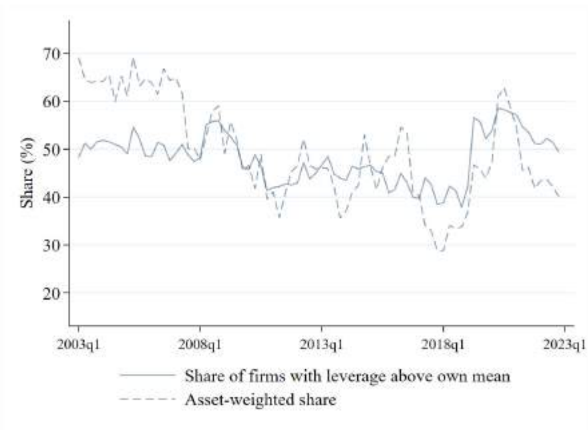
(b) Euro area



(c) United States



(d) Euro area

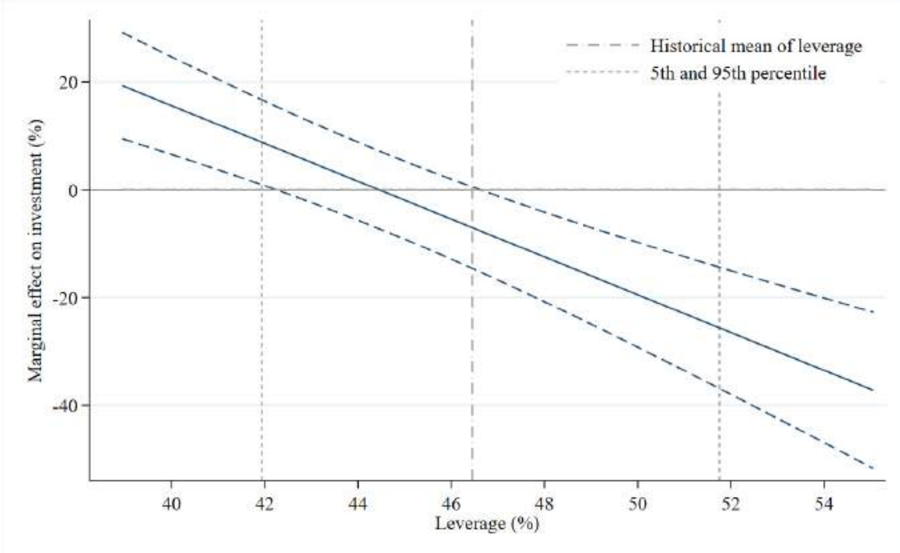


Notes: Top panels: Percentiles of leverage (defined as total liabilities relative to total assets) across firms in the sample, over time. Panel (a) compares the time series to the ratio of aggregate liabilities to aggregate assets in the US financial accounts. Bottom panels: Share of firms with leverage above the within-firm mean, unweighted and weighted by total assets.

B Details on empirical analysis and further robustness tests

B.1 Further results on local projections with aggregate time series

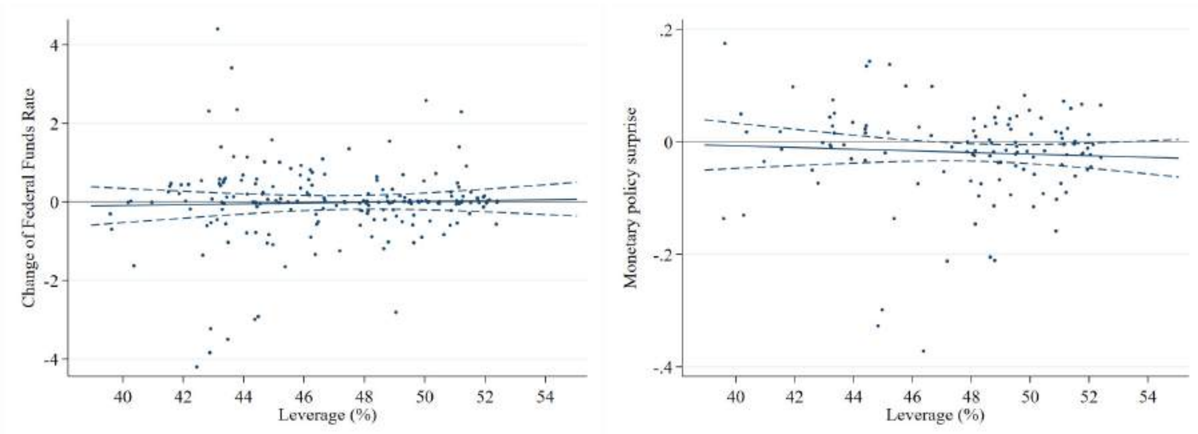
Figure B1: Semielasticity of aggregate investment to monetary policy at different leverage levels



Notes: Semielasticity of investment to a 1pp change in the short-term interest rate based on local projections (Equation (1), full impulse response shown in Figure 2), evaluated for different levels of leverage for $h = 6$. The baseline model is estimated with an interaction term $L_{t-1}\Delta R_t$, where L_{t-1} is standardized by the historical mean (ca. 46%) and standard deviation (ca. 3pp). For ease of interpretability, the x-axis shows the leverage in absolute values, along with vertical bars for the tails of historical values of leverage in the US. The 95% confidence intervals are shown as dashed lines based on HAC standard errors.

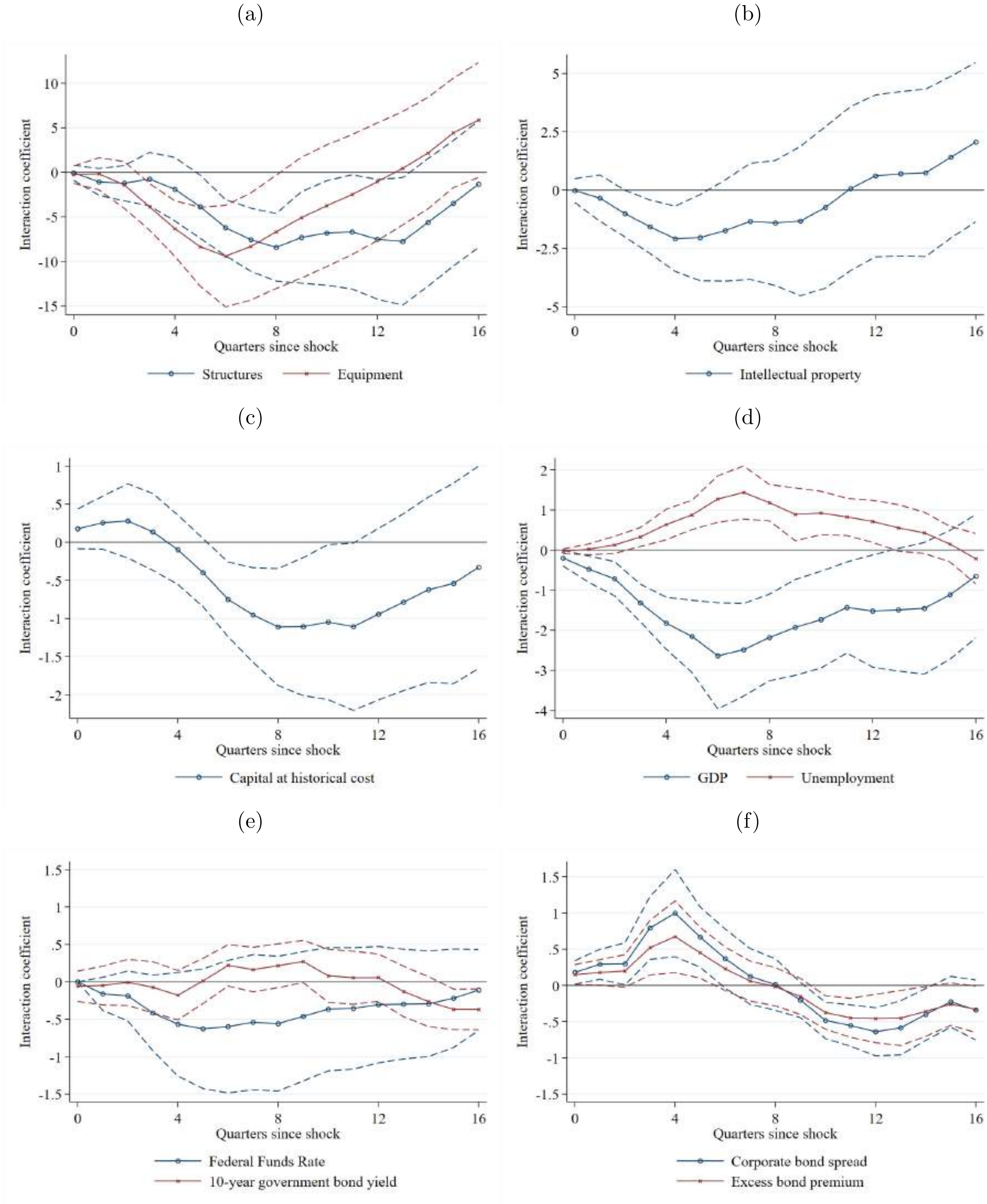
Figure B2: Randomness of monetary policy shocks

(a) ΔR_t (b) ξ_t^m



Notes: Scatter plots of the quarterly changes in the federal funds rate (a) and the Jarociński and Karadi (2020) monetary policy surprises (b), respectively, with aggregate leverage L_{t-1}, along with a fitted linear regression linear and 95% confidence intervals. The p-values on the linear slope coefficients are 0.69 and 0.52, respectively, showing that (surprise) changes in monetary policy do not seem to be systematically related to the ex-ante state of leverage in the economy.

Figure B3: State dependence of corporate leverage: Other dependent variables



Notes: Estimation results of local projections, see Equation (1), on US time series data with different dependent variables. The coefficients $\hat{\beta}_h^{\text{macro}}$ for the interaction of a standardized measure of corporate leverage with the (contractionary) monetary policy shock are shown. The definitions and sources of the data are presented in Tables A2 and A3. The 95% confidence intervals based on HAC standard errors are shown as dashed lines.

B.2 Interacted VAR

In Section 2, we use nonlinear local projections to estimate the differential effect of monetary policy on investment for different levels of leverage. In the robustness checks, we show results supporting our findings using state-dependent IRFs from an Interacted VAR (IVAR; see the bottom right panel of Figure 4). An Interacted VAR provides a parsimonious way to implement nonlinearities within a VAR setting, see, e.g. Caggiano et al. (2017) and Pellegrino et al. (2021) for applications on state-dependent effects of uncertainty shocks.

Concept. The IVAR is a linear VAR augmented with an interaction term. The presence of this interaction term allows the effect of one variable on another to depend on the level of a third variable.

$$\mathbf{Y}_t = \mathbf{c} + \sum_{j=1}^{p} \mathbf{A}_j \mathbf{Y}_{t-j} + \left(\sum_{j=1}^{p} \mathbf{b}_j \left(Y_{4,t-j} \times Y_{5,t-j} \right) \right) + \mathbf{e}_t \tag{B1}$$

$\mathbf{Y}_t$ is a vector of endogenous variables. In our case, these variables are chosen to replicate a nonlinear version of the Gertler and Karadi (2015) model augmented by leverage and investment. They include the following: GDP, the GDP deflator, investment (all in log levels), standardized leverage L_t (see 2.2), the federal funds rate, and quarterly averages of the excess bond premium by Gilchrist and Zakrajšek (2012). $\mathbf{c}$ is a vector of constant terms, $\mathbf{A}_j$ are matrices of dynamic coefficients that relate the 6 endogenous variables to one another, $\mathbf{e}_t$ is the vector of error terms with a variance-covariance matrix of $\mathbf{\Omega}$. The number of lags p is set to 4. In the IVAR, we additionally regress $\mathbf{Y}_t$ on the lags of an interaction of two variables that are themselves part of $\mathbf{Y}$, in our case, leverage (in the 4th position and therefore denoted Y_4) and the federal funds rate (Y_5).

Where does the nonlinearity in this model come from? If there is a shock to the federal funds rate $e_{5,t}$, this shock has the same direct effect on $Y_{5,t}$ as it would have in a linear VAR (though parameters might differ), regardless of the value of $Y_{4,t}$. In the subsequent period, however, the value of investment $Y_{3,t+1}$ will depend not only linearly on values of $\mathbf{Y}_t$, but also on higher-order terms, meaning that it will load on the shocked federal funds rate interacted with, in our case, lagged leverage. While the IVAR is nonlinear in variables, it is linear in parameters.

GIRFs. To compute the endogenous, potentially state-dependent dynamic response to a monetary policy shock, we compute generalized impulse response functions (GIRFs) for high- and low-leverage periods following Koop et al. (1996). Generalized impulse response functions are computed as the difference between a simulated path of an endogenous variable with and without the shock (ξ_t^m):

$$GIRF_{\mathbf{Y},t}(h, \xi_t^m, \mathcal{I}_{t-1}) = \mathbb{E}[\mathbf{Y}_{t+h} \,|\, \xi_t^m, \mathcal{I}_{t-1}] - \mathbb{E}[\mathbf{Y}_{t+h} \,|\, \mathcal{I}_{t-1}] \tag{B2}$$

$\mathcal{I}_{t-1}$ is the initial condition defined as $\{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-p}\}$. That is, for a specific initial condition, we simulate a path of the endogenous variables with a monetary policy shock and subtract from that the path absent of any shocks, i.e., the non-stochastic component of the IVAR model in Equation (B1). In practice, we consider as the set of relevant initial conditions all quarters in the historical data sample from 1973q1 to 2019q4 and simulate a GIRF specific to each initial condition. We then split all initial conditions into two subsamples at the median level of leverage and average over initial conditions such that we obtain an average GIRF for a state in which corporate leverage is elevated and one in which corporate leverage is comparatively low ($\mathcal{I}^H_{t-1}$ and $\mathcal{I}^L_{t-1}$). Figure 4 then shows the state dependence of investment as the difference between the two GIRFs:

$$\mathbb{E}[GIRF_{\mathbf{Y},t}(h, \xi^m_t, \mathcal{I}_{t-1} \in \mathcal{I}^H_{t-1})] - \mathbb{E}[GIRF_{\mathbf{Y},t}(h, \xi^m_t, \mathcal{I}_{t-1} \in \mathcal{I}^L_{t-1})] \tag{B3}$$

The algorithm to calculate state-dependent GIRFs and bootstrapped confidence intervals is listed at the end of the section.

Advantages. An advantage of the IVAR is that it relies only on observable parameters and can be estimated with OLS over the full sample. The number of parameters stays relatively limited compared to, for example, smooth-transition VARs, as there is only one additional vector of estimates $\mathbf{b}$ with p elements and only one variance-covariance matrix of the error terms. Another advantage relevant in our case is that for the purpose of identification, the observations used for identification can be decoupled from the estimation sample, allowing us to use the full range of the available time series (1973q1 to 2019q4). We describe how we identify the structural shocks from the reduced-form residuals further below.

Disadvantages. We see the drawbacks of the IVAR as relatively limited. First, one constraint is that to allow for nonlinear effects, the "shocked" variable Y_5 and the "state" variable Y_4 both need to be elements of $\mathbf{Y}_t$. This limits the inclusion of other potential interaction terms, as the system of equations would quickly become too high-dimensional. Second, as we estimate only one variance-covariance matrix, the effect of a shock to $e_{5,t}$ on $\mathbf{Y}_t$ will be independent of $Y_{4,t-j}$. Thus, we are not able to uncover potential state dependence in the impact response. In the present case, this inability should not be a major concern, as all our results based on local projections in Section 2.3 indicate that the state dependence unfolds in the medium-run, which the IVAR should be able to capture well.

Identification. The estimated residuals $\hat{\mathbf{e}}_t$ will be correlated across variables. Therefore, the residuals of the federal funds rate equation $\hat{e}_{5,t}$ cannot be interpreted as structural monetary policy shocks. We implement two identification strategies to retrieve the structural shocks, which we denote ε_t. The first is a traditional Cholesky decomposition, which has been implemented in the context of an Interacted VAR before. We assume the following relationship: $\mathbf{e}_t = \mathbf{S}\varepsilon_t$, where $\mathbf{S}$ is a lower-diagonal matrix obtained through a Cholesky decomposition on $\hat{\mathbf{\Omega}} = \mathbf{SS}'$. The ordering of variables is as described above, with the federal funds rate ordered last just before the excess bond premium. This ordering restricts the response of most variables after a monetary policy shock to be zero on impact (regardless of the initial condition).

We corroborate our findings with a version of the Interacted VAR where shocks to monetary policy are identified with the help of an external instrument. We start from the relationship $\mathbf{e}_t = \mathbf{s}\varepsilon_t$, where $\mathbf{s}$ is now a vector instead of a matrix because only one shock is identified. The instrumental variable should be correlated to the true underlying monetary policy shock ξ_t^m but orthogonal to all underlying shocks. We use the Jarociński and Karadi (2020) high-frequency announcement surprises to identify this shock. As they measure market surprises during very narrow windows around FOMC announcements, they are unlikely to be correlated with other shocks to the economy. As in Gertler and Karadi (2015), we regress the reduced-form residuals associated with the federal funds rate $\hat{e}_{5,t}$ on the surprises ξ_t^m and regress the fitted value of that regression on the reduced-form residuals of the remaining variables $\hat{e}_{-5,t}$. The resulting coefficients identify the non-monetary policy shock elements of $\mathbf{s}$ to a unit ξ_t^m shock.

Full algorithm. Outline of the estimation algorithm including the bootstrapping procedure (see also the Online Appendix to Pellegrino et al. (2021)):

1. Pick an initial condition $\mathcal{I}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-p}\}$, i.e., the historical values of the lagged endogenous variables at a particular date t. Notice that this set includes the values for the interaction terms;

2. Randomly (with repetition) sample a sequence of H residuals from the empirical distribution d(0,$\hat{\mathbf{\Omega}}$), where $\hat{\mathbf{\Omega}}$ is the estimated variance-covariance matrix of residuals. These residuals are referred to as $\tilde{\mathbf{e}}_{t+h}$;

3. Conditional on $\mathcal{I}_{t-1}$ and on the estimated model (B1), obtain the path $\tilde{\mathbf{Y}}_{t+h}$ for $h = 0, 1, ..., H$ by simulating the model with the reduced-form residuals $\tilde{\mathbf{e}}_{t+h}$ forward;

4. Conditional on $\mathcal{I}_{t-1}$ and on the estimated model (B1), obtain the path $\tilde{\mathbf{Y}}_{t+h}^{\xi^m}$ for $h = 0, 1, ..., H$ by simulating the model forward, imposing a structural shock on $\tilde{\mathbf{e}}_{t+h}$ in $t = 0$. The exact implementation differs across identification strategies:

   (a) Cholesky decomposition: Recover the structural shock associated with $\tilde{\mathbf{e}}_{t+h}$ by $\tilde{\varepsilon}_t = \mathbf{S}^{-1}\tilde{\mathbf{e}}_t$, where $\mathbf{S}$ is the lower-diagonal matrix obtained from the Cholesky decomposition (see "Identification above"). Add a unit quantity to the scalar element that refers to the monetary policy rate: $\tilde{\varepsilon}_{5,t}^{\xi^m} = \tilde{\varepsilon}_{5,t} + 1$. Compute the reduced-form residuals consistent with this added shock $\tilde{\mathbf{e}}_t^{\xi^m} = \mathbf{S}\tilde{\varepsilon}_t^{\xi^m}$ and proceed as in Step 3;

   (b) External instrument: Recover the matrix $\mathbf{s}$ from the reduced-form residuals (see "Identification" above), compute $\tilde{\mathbf{e}}_t^{\xi^m} = \tilde{\mathbf{e}}_t + \mathbf{s}$ and proceed as in Step 3;

5. Compute the difference between the two paths;$\tilde{\mathbf{Y}}_{t+h}^{\xi^m} - \tilde{\mathbf{Y}}_{t+h}$;

6. Repeat Steps 2-5 for 1,000 draws from d(0,$\hat{\mathbf{\Omega}}$), and compute the average across draws. Notice that, in this computation, the starting month $t-1$ does not change. In this way, we obtain a consistent point estimate of the GIRF for each given starting month in our sample, i.e., $GIRF_{\mathbf{Y},t}(h, \xi_t^m, \mathcal{I}_{t-1})$. If a given initial condition leads to an explosive response, it would be discarded. However, there are no explosive GIRFs in our applications;

7. Repeat Steps 2-6 for each initial condition, i.e., for each period in the historical sample;

8. Split the sample of initial conditions into subsamples. In our applications, we consider as equally-sized subsamples the initial conditions with leverage (see Section 2.2 for the definition) above and below the historical median. We refer to them as $\mathcal{I}^H_{t-1}$ and $\mathcal{I}^L_{t-1}$. We then average the obtained GIRFs across initial conditions within the subgroup: $GIRF^H_{\mathbf{Y}} = \mathbb{E}[GIRF_{\mathbf{Y},t}(h, \xi^m_t, \mathcal{I}_{t-1} \in \mathcal{I}^H_{t-1})]$, and equivalently for $GIRF^L_{\mathbf{Y}}$; to obtain the degree of state dependence of monetary policy between the high- and low-leverage monetary policy regime, subtract $GIRF^H_{\mathbf{Y}} - GIRF^L_{\mathbf{Y}}$;

9. Obtain confidence intervals via bootstrapping with 1,000 draws. The bootstrapping algorithm differs across identification strategies:

   (a) Cholesky decomposition: Randomly (with repetition) sample a sequence of T residuals from the empirical distribution d(0,$\hat{\mathbf{\Omega}}$).

   (b) External instrument: When identifying structural shocks with external instruments, the ordering of the time period needs to be preserved. Therefore, we implement a Wild bootstrap (Wu, 1986) with a Rademacher distribution that flips the sign of a randomly selected subset comprising 50% of residuals.

   Simulate a dataset using model (B1) and the sampled residuals, constructing the interaction of endogenous variables in the process. Repeat Steps 1-8 for each draw. Replace draws generating explosive data series or GIRFs.

B.3 Aggregate local projections with Romer & Romer shocks

In our main specification, we used Jarociński and Karadi (2020)'s high-frequency monetary policy surprises, which are adjusted for information effects of monetary policy. Here, we show that the main result does not depend on the choice of these shocks.

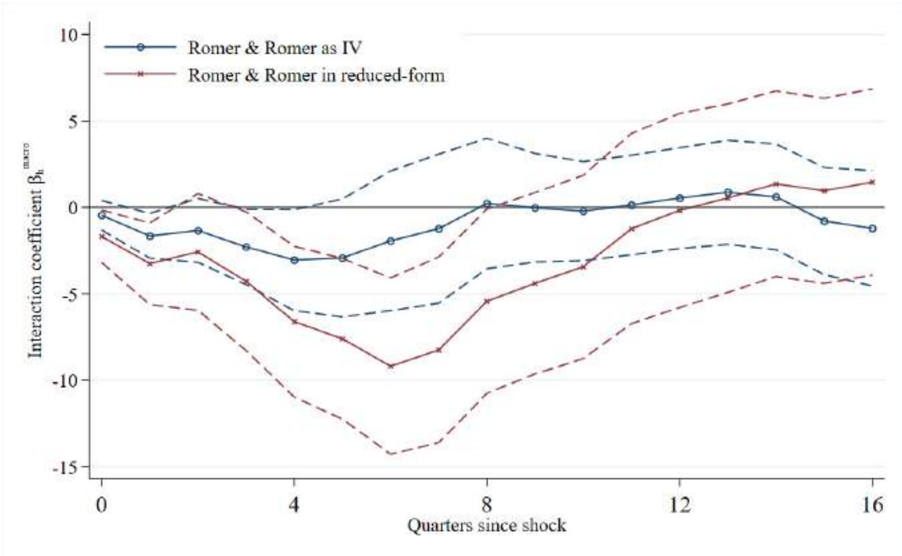
We use Romer and Romer (2004) shocks as ξ^m_t, the instrument affecting the federal funds rate instead. These surprises are the residuals of a regression of the federal funds rate on Greenbook (now Tealbook) forecasts. They proxy changes in the federal funds rate that are orthogonal to and surprising given the Federal Reserve Board Governors' macroeconomic projections. We use the shocks from 1973q1 extended to 2007q4 by Wieland and Yang (2020). This has the appealing side effect that we can extend the data sample significantly backwards relative to our baseline sample, which covers the period 1990q1-2019q4. The left-hand panel of Figure B4 shows that $\hat{\beta}^{\text{macro}}_t$ is statistically significantly negative, as in our main estimation. Quantitatively, the estimate is smaller (approximately -3%), but the trough of the linear coefficient $\hat{\alpha}_t$ (not shown) is approximately -4%, making monetary policy almost twice as powerful when corporate leverage is elevated by one standard deviation.

Instead of using these shocks to identify $\hat{\beta}^{\text{macro}}_t$ in Equation (1), we can estimate a reduced-form specification:

$$I_{t+h} - I_{t-1} = c_h + \alpha_h \, \xi_t^m + \beta_h^{\text{macro}} \, L_{t-1} \, \xi_t^m + \boldsymbol{\Gamma'}_h \mathbf{Z}_{t-1} + e_t, \tag{B4}$$

The resulting $\hat{\beta}_t^{\text{macro}}$ is shown with the red lines in Figure B4. Our reduced-form estimates are in line with the finding that the effects of monetary policy on investment are twice as large when corporate leverage is one standard deviation above its historical mean.

Figure B4: Macro elasticity with Romer & Romer shocks



Notes: Estimation results of local projections, see Equation (1) and (B4), on US time series data for investment, with Romer and Romer (2004) shocks from 1973q1 to 2007q4 acting as ξ_t^m. The coefficients $\hat{\beta}_h^{\text{macro}}$ for the interaction of a standardized measure of corporate leverage with the (contractionary) monetary policy shock are shown. The 95% confidence intervals based on HAC standard errors are shown as dashed lines.

B.4 Evidence from euro area time series

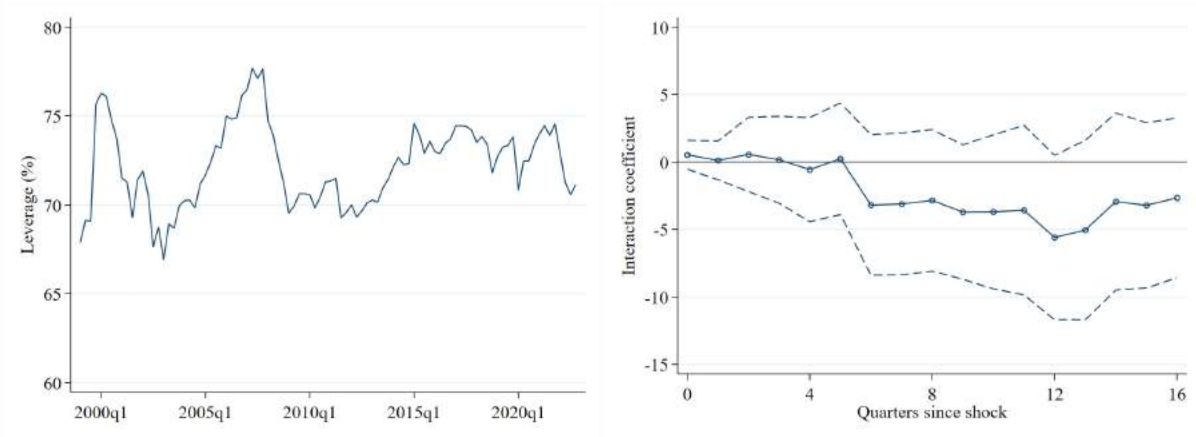
We estimate Equation (1) for euro area time series as well. The data sources are listed in Table B1. The estimated medium-run coefficients – presented in Figure B5(b) – have the same sign as the US time series but are not statistically significant.

There are several reasons why we would expect results for the euro area to be weaker statistically than those for the US. First and foremost, the time series are shorter and provide only two full tightening cycles; moreover, the temporary interest rate increases in 2011. A shorter time span also means that for a larger share of the time, the policy rate is constrained by the lower bound. Aggregate leverage is also somewhat less volatile than in the US. It varies between 67 and 77% (see Figure B5(a)), whereas the equivalent measure for the US varies by more than 10pp. It is also possible that we measured the aggregate state of leverage somewhat less precisely in the euro area, as the two components in the numerator – financial and nonfinancial assets of corporations – derive from related but somewhat different statistics. Another reason could be that Ireland is responsible for an outsized share of the short-term fluctuations in investment

Figure B5: Results for the euro area

(a) Median corporate leverage over time

(b) Differential IRF ($\hat{\beta}_h^{\text{macro}}$)



Notes: Equivalent of Figure 2 (local projections on US time series) estimated for the euro area (starting in 1999). The 95% confidence intervals are shown as dashed lines based on HAC standard errors. The data sources are listed in Table B1.

for reasons that are unrelated to monetary policy or leverage. Noise in the dependent variable leads to efficiency losses in the estimation. Finally, an institutional reason could be responsible for the weaker euro area result. Capital markets in the euro area are not fully integrated, and the area-wide measure of corporate leverage therefore reflects national funding conditions imperfectly. Unfortunately, there exists only an area-wide measure of aggregate nonfinancial assets, preventing us from conducting the analysis at a more disaggregate level.

Auer et al. (2021) estimate similar local projections for a panel of euro area sectors and find that *output* (industrial production, not investment) responds more strongly to ECB monetary policy shocks if leverage in the sector is high. Holm-Hadulla and Thürwächter (2023) look at the interaction of monetary policy and corporate leverage shocks (rather than the level of leverage). While the data and estimation methods in these two papers are somewhat different, the results are not inconsistent with each other.

Table B1: Aggregate time series for euro area

Variable	Definition	Retrieved from	Original source	Transform.
Dependent variables				
Investment	Gross capital formation in 2015 chained euros	LSEG: EKESNGCPD	Eurostat	$100 \times \log$
Shock variables				
Euribor 3m	Euribor 3-month interest rate	LSEG: EIBOR3M	EBF	Δ
ξ_t^m	High-frequency announcement surprises	Jarociński and Karadi (2020)		
Leverage				
Financial liabilities	Financial liabilities of nonfinancial corporations	ECB DW: QSA.Q.N.I8.W0.S11.S1.N.L.LE.F._Z._Z.XDC._T.S.V.N._T	ECB, Eurostat	
Financial assets	Financial assets of nonfinancial corporations	ECB DW: QSA.Q.N.I8.W0.S11.S1.N.A.LE.F._Z._Z.XDC._T.S.V.N._T	ECB, Eurostat	
Non-financial assets	Non-financial assets of nonfinancial corporations	ECB DW: QSA.Q.N.I8.W0.S11.S1._Z.D.LE.N11G._Z._Z.XDC._Z.S.V.N._T	ECB, Eurostat	
Leverage (L)	Aggregate corp. leverage	Own calculations:	$100 \frac{\text{Fin. liab.}}{\text{Fin. ass.} + \text{Non-fin. ass.}}$	
Control variables				
GDP	Real gross domestic product in chained 2015 euros	LSEG: EKGDP...D	Eurostat	$\Delta 100 \times \log$
CPI	Consumer price index, all items	LSEG: EMEBCPALE	ECB	$\Delta 100 \times \log$
Investment price	Implicit price defl. of investment, calculated as ratio of nominal and real investment	LSEG: EKGFCF..B	Eurostat	$\Delta 100 \times \log$
Core CPI	—, all items less food and energy	LSEG: EMEBCPXFE	ECB	$\Delta 100 \times \log$
Bond spread	Corporate bond yields relative to Bund	Gilchrist and Mojon (2018)		

Notes: Values of higher-than-quarterly frequency variables are averaged within the quarter, with the exception of the 3-months Euribor rate, where we use end-of-quarter values.

B.5 Further results and robustness for the micro elasticity

This section presents and discusses robustness tests for the evidence presented in Section 3, i.e., that the semielasticity of investment to contractionary monetary policy shocks is increasing in leverage. For the sake of presentation, we display only estimates for $h = 6$ in tables, but the full impulse responses are included in the robustness section (Section 4.2). Table B2, Column (1) contains the main result for reference. It shows that capital for firms with a one standard deviation higher leverage is 8pp higher 6 quarters after a contractionary monetary policy shock than when leverage is equal to the firm's long-run mean.

Average effect: Comparing the size of these estimates to the mean is challenging because our main regression equation (2) contains sector-time and country-time fixed effects that absorb all variation that is common in time, including capital depreciation and capital price changes (valuation effects). These fixed effects are crucial for the identification of our interaction effect, but they also absorb the monetary policy shock itself, rendering the estimation of an average response to monetary policy impossible. To nevertheless provide an estimate of the average response, we estimate another version of our local projections in Column (2):

$$\log k_{i,t+h} - \log k_{i,t-1} = \alpha_h^{\text{micro}} \xi_{ct}^m + \beta_h^{\text{micro}} \left(\frac{\ell_{i,t-1} - \bar{\ell}_i}{\sigma_{\ell,i}}\right) \xi_{ct}^m + \mathbf{\Gamma}'_h \mathbf{Z}_{i,t-1} + \mathbf{\Delta}'_h \mathbf{Y}_{c,t-1} + \zeta_{ih} + \eta_{sth} + e_{ith} \tag{B5}$$

Compared to equation (2), we include the average response α_h^{micro} and in return, replace the country-time fixed effect θ_{ct} with macroeconomic time series information in $\mathbf{Y}_{c,t-1}$. The vector includes four lags of the GDP and aggregate investment growth rates, the unemployment rate, changes in policy rates as well as inflation in terms of the CPI and GDP deflators of the respective region c. The exclusion of country-time fixed effects allows us to still include the crucial sector-time fixed effects while estimating an average response α_h^{micro} because there is cross-country variation in monetary policy shocks. In other words, the average response is identified from the fact that Jarociński and Karadi (2020) monetary policy shocks differ between the US and the euro area. Column (2) of Table B2 shows that the average response of capital to a 1pp exogenous increase in the monetary policy rate is estimated to be -5%, although the effects are not statistically significantly different from zero. Meanwhile, the estimate of the interaction coefficient remains statistically significantly positive. The point estimate is well within the range found in the literature. For example, Ottonello and Winberry (2020) find an average capital response to an exogenous 1pp increase in the monetary policy rate of -3%, Cloyne et al. (2020)'s estimates of the investment rate imply a capital response with a similar size to ours,[22] whereas Lakdawala and Moreland (forthcoming) report that a one-standard deviation monetary policy shock (of 9bps) leads to an average decrease in large firms' capital stock by approximately 1.2% in the medium run, which is substantially larger than our estimate when scaled to a 1pp rate

[22] They report the average response of the investment *rate* to a 25bp increase in the interest rate. Based on a quarterly depreciation (and therefore, in steady state, reinvestment) rate of 3%, we compute the implied path of the capital stock. After 6 quarters, the capital stock has decreased by approximately 1%, implying a response of -4% to a 1pp rate hike.

Table B2: Differential response of capital to monetary policy for $h = 6$

	(1) Baseline	(2) incl. mean	(3) United States	(4) Euro area	(5) Time/smpl. weights	(6) OW20
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1}$	8.37***	7.03**	11.80***	10.55**	6.49***	9.67**
	(2.88)	(2.87)	(3.26)	(5.05)	(2.65)	(3.69)
ξ^m_{ct}		-5.61				
		(5.22)				
Baseline controls	yes	yes*	yes	yes	yes	yes
Firm + sector-time FE	yes	yes	yes	yes	yes	yes
Country-time FE	yes	no	no	yes	yes	no
Observations	150,779	147,660	109,574	41,205	150,779	53,983
R^2	0.29	0.29	0.29	0.34	0.30	0.36
Firms	2,714	2,705	1,735	979	2,714	1,249
Median $\sigma_{\ell,i}$	10.15	10.15	12.22	7.11	10.15	11.94

Notes: Estimation results of panel local projections, see Equation (2) for $h = 6$. ξ^m_{ct} are the monetary policy surprises for the US and euro area, respectively; $\tilde{\ell}_{i,t-1}$ is the standardized measure of leverage (lagged liabilities to assets). Standard errors are clustered by firm and quarter. The last row reports the median standard deviation of leverage among all firms included in the respective regression. Column (2) estimates Equation (B5) to estimate the mean response of capital to monetary policy. Column (5) applies regression weights, overweighting firms in the euro area and earlier in the sample such that all region-quarters have the same weight in the estimation of the coefficient. Column (6) uses the same principle as Ottonello and Winberry (2020) to subset the data; i.e., it uses US firms prior to the global financial crisis period only, although our sample becomes smaller than theirs because of stricter firm selection. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

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Subsamples by region and time: Columns (3) and (4) of Table B2 show subsets of results for the US and the euro area, the complete IRFs for which are already presented in Section 4.2. Our data sample is by construction growing over time, as depicted in Figure A1. Therefore, our regressions are based on a panel that has more observations in later periods than in earlier periods. To show that this distribution does not meaningfully impact the results, we assign regression weights that are equal to half the inverse of the number of firms observed by period and region. In other words, each quarter and region receive equal weight in the estimation of β^{micro}_h. Column (5) of Table B2 shows that the interaction estimate decreases somewhat, but it remains statistically significantly positive. Finally, Column (6) drops all euro area firms and all data after 2008, including for the computation of means and standard deviations of leverage and therefore aligns most closely with the time sample used in OW20.

Definitions and transformation of leverage: In Table B3 we show that the positive interaction coefficient does not depend on the definition of leverage. First, we replace the definition of ℓ_{it} to be the ratio of debt to assets, as in OW20. Debt obligations are a subset of liabilities accounting for approximately half of all liabilities for the average firm (see Section 2.2 for a discussion). The resulting $\tilde{\ell}_{i,t}$ has a correlation with our baseline measure of only 0.7. In Column (2), we use only short-term liabilities to calculate leverage. In the US, short-term leverage is slightly less than half of our baseline leverage measure, whereas in the euro area, it is slightly more

Table B3: Micro elasticity estimated with different leverage measures

	(1) Debt/ assets	(2) Short-term liab./ass.	(3) Liabilities/ earnings	(4) Liabilities/ assets	(5) Debt/ assets
$\xi_{ct}^m \times \tilde{\ell}_{i,t-1}$	6.45***	5.91**	13.13***		
	(2.43)	(2.61)	(4.14)		
$\xi_{ct}^m \times (\ell_{i,t-1} - \bar{\ell}_i)/\bar{\sigma}_\ell$				4.94**	2.48*
				(2.07)	(1.29)
Baseline controls	yes	yes	yes	yes	yes
Firm, sectr-time, ctry-time FE	yes	yes	yes	yes	yes
Observations	138,998	150,703	142,976	150,779	139,948
R^2	0.29	0.29	0.30	0.29	0.29
Firms	2,448	2,713	2,581	2,714	2,471
Median $\sigma_{\ell,i}$	8.89	10.16	56.97		

Notes: Estimation results of panel local projections, see Equation (2) for $h = 6$. ξ_{ct}^m are the monetary policy surprises for the US and euro area, respectively; $\tilde{\ell}_{i,t-1}$ is the standardized measure of leverage, which we vary for different columns. Standard errors are clustered by firm and quarter. The last row reports the median standard deviation of leverage among all firms included in the respective regression. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

than half (see Table A4). The correlation between leverage and short-term leverage is 0.45. As before, the measure is standardized using the firm-level averages and standard deviations. In Column (3), we define the leverage as the ratio of total liabilities to a four-quarter moving sum of earnings to account for the fact that lending constraints might be based on earnings or cash flow rather than assets. The correlation with the standard leverage measure is 0.50. For all three alternative definitions of leverage, β_h^{micro} is estimated to be positive.

We prefer to standardize the interaction variable using the firm-specific standard deviation; i.e., $\tilde{\ell}_{i,t} = \frac{\ell_{it} - \bar{\ell}_i}{\sigma_{\ell,i}}$, which has the advantage of downscaling the variation in firms with highly volatile leverage, likely due to measurement error. However, our result does not depend on this standardization. In Columns (4) and (5) of Table B3, we instead include a version that is only demeaned ($\ell_{it} - \bar{\ell}_i$), after winsorizing at the 1st and 99th percentiles across the panel. To compare magnitudes, we divide this deviation by the standard deviation of ℓ over the full sample. In this version, we still only exploit within-firm variation in leverage. As argued by Ottonello and Winberry (2020), this approach is important to avoid the results being driven by permanent firm-level heterogeneity in the responsiveness to (monetary policy) shocks. Indeed, when we include the untransformed definition of leverage, the interaction coefficient becomes statistically insignificant (not shown) but remains positive.

NAICS fixed effects: Firms are allocated to 7 broad economic sectors by LSEG (e.g. consumer (non-)cyclicals, basic materials or industrials) and 106 finer subcategories (e.g. drug retailers, food retail and distribution, discount stores; construction and engineering, construction material). The categorization of the broad sectors is based on the type of goods and services offered by the firm and the cyclicality of their demand, i.e., relevant metrics for equity analysts. However, they could be too broad. For example, "industrials" contains industries as diverse as airlines, business support services, or vehicle manufacturing. At the same time, finer categorization (e.g. construction and engineering; homebuilding) often contains few firms in each sector. As a middle way and to better reflect the categorization in the national accounts, we manually review the 106 LSEG subsectors and allocate them to a 2017-NAICS industry. For most sectors, we match the closest possible 2-digit NAICS industry (e.g. 23 construction firms, 48 transportation firms), but for manufacturing and retail, we opt for a finer 3-digit classification (e.g. 311 food manufacturing, 312 beverage and tobacco product manufacturing; 441 motor vehicle and parts dealers, 442 furniture and home furnishing stores, etc.). We end up with 37 industries, of which the mean (median) contains 73 (57) firms. However, the estimated interaction coefficient – shown in Column (1) of Table B4 – hardly changes if we apply these 37, instead of 7, sector-time fixed effects. The R^2 of the regression increases from 0.29 to 0.31 only, indicating that the broad economic sectors are a good enough approximation to absorb the cyclical dynamics of industries.

2SLS: Following OW20, we implement almost all estimations as reduced-form regressions, estimating the effect of ξ^m_{ct} on firm-level outcome variables directly. In our macro analysis, we instead opt for a 2SLS estimation. For completeness and comparison, we implement the equivalent 2SLS estimator for the firm-level regression and instrument $\Delta R_{ct} \times \tilde{\ell}_{i,t-1}$ with $\xi^m_{ct} \times \tilde{\ell}_{i,t-1}$. The estimated coefficient, shown in Column (2), is somewhat smaller but still statistically significantly positive.

Spurious interaction effects: Balli and Sørensen (2013) discuss that regressions with interaction variables and grouped fixed effects often lead to spurious correlation. Their proposed solution is to demean the interaction variable(s) by any fixed effects included in the model. Therefore, besides subtracting the firm mean from the leverage measure as we do in the baseline specification, we additionally subtract the country-quarter and sector-quarter means before standardization. Of course, we cannot subtract these means from the monetary policy shocks because they are common in time. The results are robust, as shown in Column (3) of Table B4.

Pre/post global financial crisis: Lakdawala and Moreland (2021) find that while the interaction coefficient of monetary policy shocks and lagged firm-level leverage is positive for the period before the global financial crisis, the heterogeneity might be reversed in the following period. In Column (4) of Table B4 we add an additional interaction term $\delta_h \xi^m_{ct} \tilde{\ell}_{i,t-1} D^{post}$, where D^{post} is a dummy equal to zero from 1992q3 to 2008q2 and 1 from 2009q3 onward and missing during the Great Recession. While the estimate of β^{macro}_h for the pre-crisis period remains almost unchanged and statistically significantly different from zero, the additional effect for the period after the global financial crisis seems to be, if anything, positive, although the standard errors are large and not statistically significant.

Asset redeployability: We include as another cross-covariate term the sector-level measure of redeployability of assets proposed by Kim and Kung (2017), which provides insights into both the versatility and the depth of a second-hand market for an asset. Kim and Kung (2017) find that firms using highly specialized assets as capital inputs into production – i.e., those with low

Table B4: Robustness of firm-level results to specification

	(1) NAICS fixed effects	(2) 2SLS	(3) Triple demean	(4) Pre/post GFC	(5) Asset re-deployability
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1}$	8.09***	5.84**	6.86**	7.49**	8.06***
	(2.82)	(2.72)	(2.74)	(3.09)	(2.90)
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1} \times D^{\text{post}}$				5.83	
				(8.78)	
$\xi^m_{ct} \times \theta_s$					-2.71
					(3.92)
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1} \times \theta_s$					-2.39
					(2.05)
Baseline controls	yes	yes	yes	yes	yes
Firm, sectr-time, ctry-time FE	yes	yes	yes	yes	yes
Observations	150,621	150,779	150,779	143,398	150,779
R^2	0.31	0.14	0.29	0.30	0.29
Firms	2,714	2,714	2,714	2,713	2,714
Sectors	37	7	7	7	7
Median $\sigma_{\ell,i}$	10.15	10.15	10.15	10.15	10.15

Notes: Estimation results of panel local projections, see Equation (2) for $h = 6$. ξ^m_{ct} are the monetary policy surprises for the US and euro area, respectively; $\tilde{\ell}_{i,t-1}$ is the standardized measure of leverage (liabilities relative to assets). Standard errors are clustered by firm and quarter. The last row reports the median standard deviation of leverage among all firms included in the respective regression. Column (4) uses a dummy variable for the post-global financial period. Column (5) adds interaction terms with the asset redeployability score provided by Kim and Kung (2017), standardized across all industries. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

redeployability – are more responsive to uncertainty shocks than those with high redeployability. Using specialized assets means that future capital adjustment is more costly, and thus an increase in uncertainty has a larger effect on these firms' expected investment return. Lakdawala and Moreland (forthcoming) find that firms facing higher ex-ante uncertainty respond less to monetary policy, especially when they have a capital stock with low redeployability. In our estimation, the differential effect of leverage is robust to controlling for a triple interaction of the redeployability ratio θ_s, the monetary policy shock and firms' lagged leverage, whose estimands are shown in Column (5) of Table B4. Even though the triple interaction term is not statistically significant, the point estimate is negative, which shows that the difference between high- and low-leverage firms is muted in sectors with high redeployability and particularly pronounced in sectors with specialized assets.

Confounding factors related to firm dynamics: We show that the result that low-leverage firms are more responsive to monetary policy is not driven by differences in firm age or other firm characteristics related to firm dynamics, particularly the availability of liquid assets. Cloyne et al. (2023) show that young firms not paying dividends adjust capital expenditure and borrowing more in response to changes in the interest rate. In principle, if young firms have lower leverage, this might confound our results. Notice, however, that Cloyne et al. (2023) find no significant pattern regarding age over the firm life cycle in the Compustat data. Ottonello and Winberry (2020), on the other hand, calibrate their heterogeneous firm New Keynesian model to moments

Table B5: Firm-level results controlling for other firm dynamics (for $h = 6$)

	(1) Add liquidity	(2) Add age	(3) Age within	(4) Young dummy	(5) Dynamic dummy
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1}$	8.40***	8.41***	8.40***	8.31***	8.19***
	(2.90)	(2.90)	(2.90)	(2.86)	(2.74)
$\xi^m_{ct} \times c_{i,t-1}$	0.08	0.08	0.08	0.09	0.09
	(0.18)	(0.18)	(0.18)	(0.18)	(0.19)
$\xi^m_{ct} \times a_{i,t-1}$		-0.43			
		(0.85)			
$\xi^m_{ct} \times (a_{i,t-1} - \bar{a}_i)$			-0.36		
			(1.51)		
$\xi^m_{ct} \times \mathbb{1}[a_{i,t-1} < 5]$				-8.50	
				(10.37)	
$\xi^m_{ct} \times \mathbb{1}[\text{Dynamic firm}]_{i,t-1}$					-8.58
					(13.05)
Baseline controls	yes	yes	yes	yes	yes
Firm, sectr-time, ctry-time FE	yes	yes	yes	yes	yes
Observations	150,779	150,779	150,779	150,779	150,779
R^2	0.29	0.29	0.29	0.29	0.29
Firms	2,714	2,714	2,714	2,714	2,714

Notes: Estimation results of panel local projections, see Equation (2) for $h = 6$, with different additional interactions of the monetary policy shock with measures of firm age a. We do not observe actual firm age and instead include the firm's tenure in the sample, which is a linear function of actual firm age. The "dynamic firm" dummy used in Column (5) is equal to one if two conditions are satisfied: First, current deflated assets are below the firm's overall sample mean, and second, the 4-quarter moving average growth rate of real assets is above the firm's sample mean. The overlap with the "young firm" dummy (firms that have been listed in the data for fewer than five years) is approximately 68%. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

of the Compustat firm sample. In their model, firms are born with low leverage, quickly take on high leverage to grow and then deleverage as they mature. In such a case – where older firms have lower leverage – our interaction coefficients would be biased down, and therefore, the difference between micro and macro elasticities would increase.

We conduct several alterations to our baseline estimation by including the ratio of liquid to total assets – following Jeenas (2024) – as well as age, or functions thereof, interacted with the monetary policy shock. We present the results in Table B5. Importantly, however, we do not observe firm age in our data, which covers only listed firms. Instead, we know in which quarter the firm became listed, in case it occurred after the beginning of the sample in 1992. The difference between the quarter of observation and the quarter of first observation is a linear function of the firm's true age. Interactions of monetary policy shocks with this (imperfect) firm age measure are generally not statistically significant, but the coefficients for leverage interactions remain both quantitatively and statistically significant. We find that the firms in our data have an elevated growth rate of capital in approximately the first five years they are in the data and therefore add an interaction with monetary policy shocks and a dummy for whether or not the firm has been in the data for fewer than five years (see "young dummy" in Column (4)). These modifications do not change our main results. Finally, we define a dummy

Table B6: Robustness of firm-level results to shock identification (for $h = 6$)

	(1) All	(2) United States	(3)	(4) Euro area	(5)	(6)
	incl. CBI component	"Smoothed" shocks	as published (-2016)	"Smoothed" shocks	as published (-2016)	US shocks
$\xi_{ct}^m \times \tilde{\ell}_{i,t-1}$	9.81***	6.95***	12.18***	7.66*	15.84**	5.28*
	(2.64)	(1.60)	(3.59)	(3.89)	(7.31)	(2.97)
Baseline controls	yes	yes	yes	yes	yes	yes
Firm + sec.-t. FE	yes	yes	yes	yes	yes	yes
Country-time FE	yes	no	no	yes	yes	yes
Observations	150,779	109,574	102,967	41,205	35,764	41,205
R^2	0.29	0.29	0.29	0.34	0.36	0.33
Firms	2,714	1,735	1,667	979	926	979
Median $\sigma_{\ell,i}$	10.15	12.22	12.21	7.11	7.21	7.11
Std.dev.(ξ_{ct}^m)	0.095	0.113	0.077	0.066	0.045	0.060
Corr. w/ BL shock	0.85	0.85	0.97	0.88	0.87	-0.005

Notes: Estimation results of panel local projections, see Equation (2) for $h = 6$, with robustness in terms of the high-frequency identified shocks. Column (1) uses the quarterly sum of the "raw" Jarociński and Karadi (2020) high-frequency interest rate changes around monetary policy announcements, i.e., not isolated from a potential central bank information (CBI) component. For Columns (2) and (4), we follow Ottonello and Winberry (2020) and weight the shocks for how early in the quarter they occur: $\sum_\tau (1 - (\tau_{ct}^d/\tau_t^n))\xi_{c\tau}^m$, where τ is an index for each monetary policy communication by the FOMC or the ECB, τ_{ct}^d is the day in the quarter of that announcement and τ_t^n is the total number of days in quarter t. In Columns (3) and (5), we use the non-extended shocks as they are published in the Online Appendix to Jarociński and Karadi (2020). Column (6) uses the US shocks for all firms, accounting for the fact that globally operating European firms are affected by US monetary policy as well. While the p-value for $h = 6$ shown above is 0.08, all estimates between quarters 7 and 16 are significant at the 5% level. The last row contains the correlation coefficient between the shocks used in the respective column and the baseline specification. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

"dynamic firm" equal to one if the firm showed an extraordinarily high growth rate around that period, e.g. because it is a startup or because it merged with another firm. The idea is to capture firms that currently operate substantially below their steady state level of capital. While we find that these dynamic firms respond somewhat more to monetary policy (although not in a statistically significant way), our $\hat{\beta}_h^{\text{micro}}$ interaction coefficient remains statistically significantly positive.

Monetary policy shocks: We also show that the positive β_h^{micro} estimates are not unique to the way we use monetary policy shocks by using different measures of high-frequency monetary policy shocks. In particular, we apply the smoothing function to the daily monetary policy shocks as they happen within the quarter, similar to OW20. In our baseline specification, we calculated simple sums of potentially multiple shocks in a quarter because we are predominantly interested in the medium-term response of investment rather than the contemporaneous response as OW20 are. For the medium-term response, the date of the shock within a quarter presumably plays less of a role than for the within-quarter response. However, our results are robust to using the smoothed shocks as well. Our results are also not driven by the fact that high-frequency, information-effect-cleaned shocks were updated by Jarociński and Karadi (2020) after the initial publication. Results for euro area firms are even robust to using US monetary policy shocks

Table B7: Firm-level results by broad economic sector (for $h = 6$)

	(1) Basic metals	(2) Consumer cyclicals	(3) Cons. non-cycl.	(4) Energy	(5) Health-care	(6) Indus-trials	(7) Tech-nology
$\xi^m_{ct} \times \tilde{\ell}_{i,t-1}$	-2.70	9.99*	-7.50*	7.34	15.61*	6.27	13.48**
	(2.82)	(5.22)	(3.94)	(5.55)	(8.13)	(4.51)	(5.16)
Baseline controls	yes	yes	yes	yes	yes	yes	yes
Firm + NAICS-time FE	yes	yes	yes	yes	yes	yes	yes
Country-time FE	yes	yes	yes	yes	yes	yes	yes
Observations	13,413	31,623	12,397	10,448	19,301	33,623	29,343
R^2	0.38	0.37	0.37	0.44	0.29	0.28	0.33
Firms	238	561	205	193	399	566	549
Sectors	1	1	1	1	1	1	1
Median $\sigma_{\ell,i}$	7.80	9.82	7.96	11.52	15.78	8.74	11.33

Notes: Estimation of Equation (2) for each of the 7 broad economic sectors separately. The financial, real estate and utilities sectors were excluded from the sample. Additionally, we now include NAICS-time fixed effects that are nested within these sectors. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

(see Column (6) of Table B6).

Sectors: We estimate Equation (2) for each of the seven broad economic sectors separately and present the results separately in the columns of Table B7.

C Details of OW20 model with high and low aggregate leverage

C.1 Calibration

Table C1: Calibration of the OW20 economy

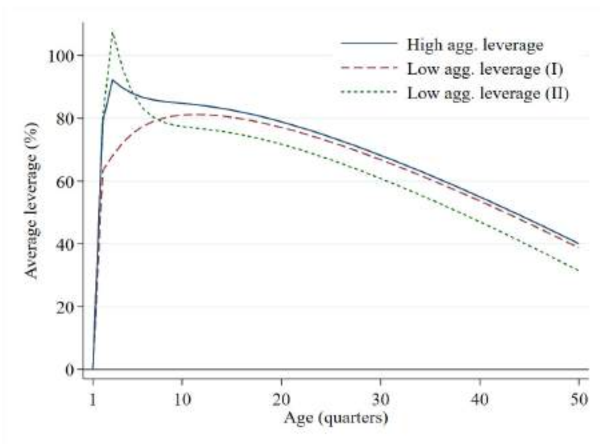
Parameter	Description	Value
Fixed parameters		
Household & firms		
β	Subjective discount factor	0.99
ν	Labor coefficient	0.64
θ	Capital coefficient	0.21
δ	Depreciation rate	0.025
New Keynesian Block		
ϕ	Aggregate capital adjustment costs	4
γ	Demand elasticity	10
φ_π	Reaction coefficient	1.25
φ	Price adjustment cost	90
Fitted parameters		
Idiosyncratic shock processes		
ρ	Persistence of TFP (fixed)	0.90
σ	SD of innovations to TFP	0.03
σ_ω	SD of capital quality	0.04
Financial frictions		
ξ	Operating cost	0.04
α	Loan recovery rate	0.54
Firm lifecycle		
m	Mean shift of entrants' prod.	3.12
k_0	Initial capital	0.18
π_d	Exogenous exit rate	0.01

Notes: All the calibration values are from Ottonello and Winberry (2020).

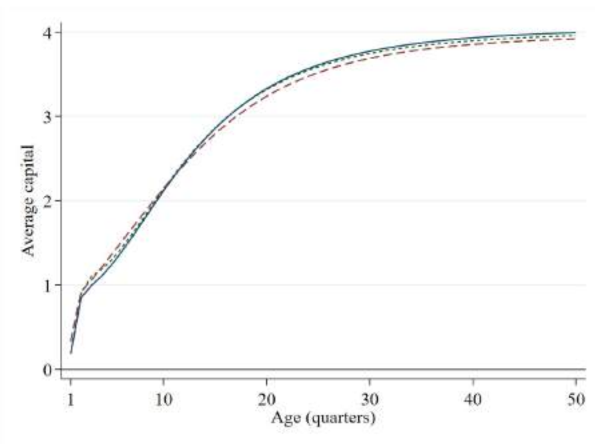
C.2 Counterfactual calibrations to vary aggregate leverage

Figure C1: Life cycle dynamics

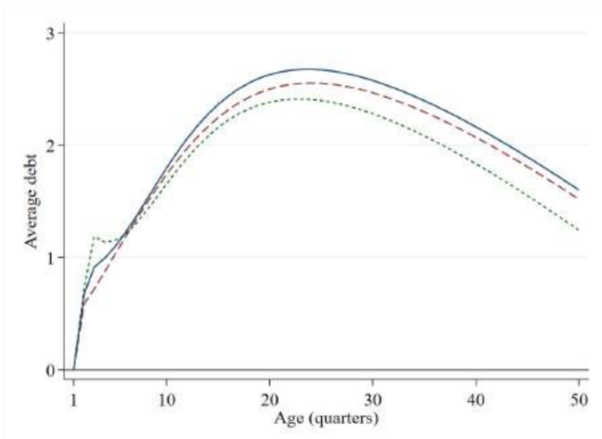
(a) Leverage



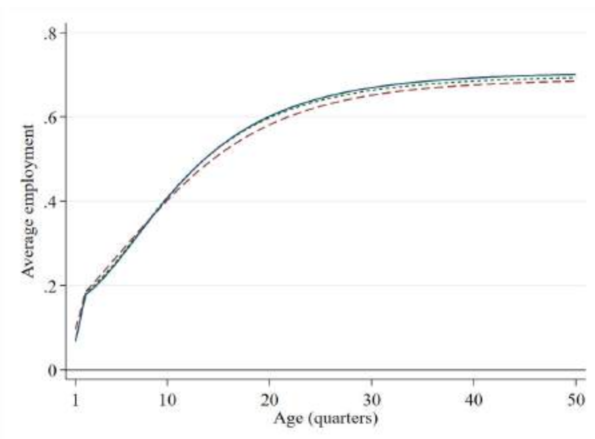
(b) Capital



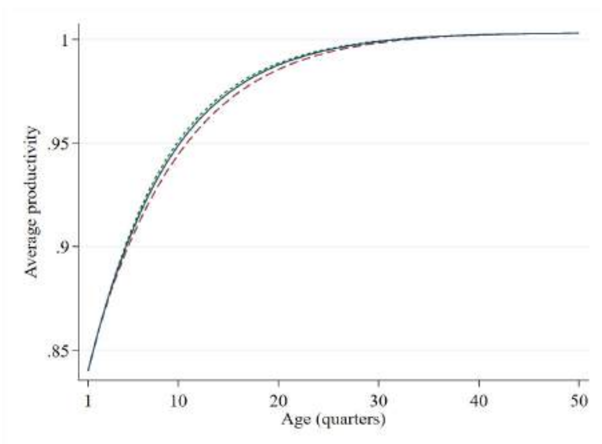
(c) Borrowing



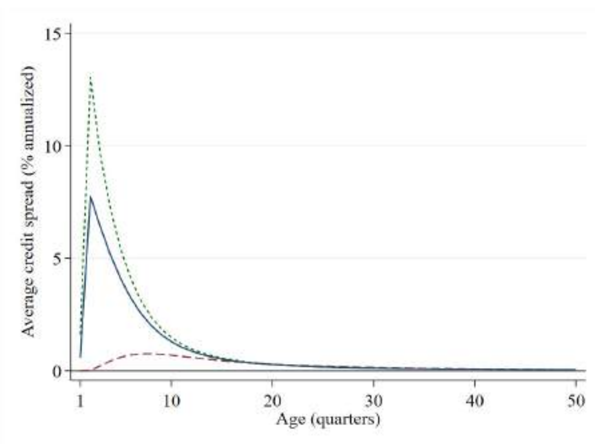
(d) Labor



(e) Productivity



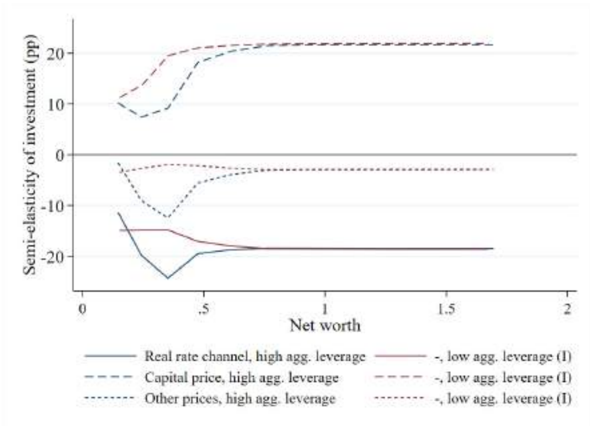
(f) Credit spread



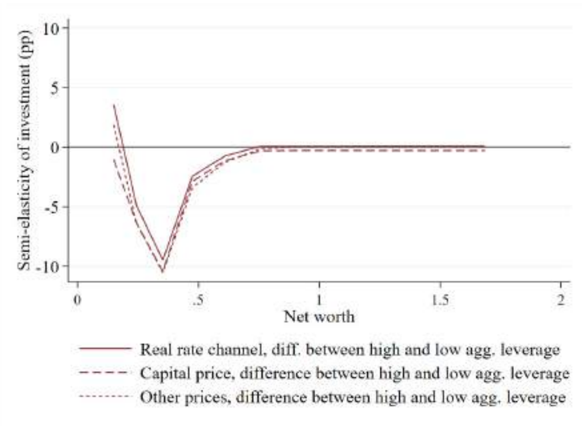
Notes: Average life cycle characteristics in the OW20 model. The average characteristics across firms by age in steady state are shown. The blue lines denote the original OW20 calibration; the dashed lines denote alterations that lead to a lower level of aggregate leverage in steady state (46% instead of 49%). "Low agg. leverage" (I) uses a higher initial level of capital k_0, while (II) uses a lower exogenous exit probability π_d. See Section 5.2.1 for details.

Figure C2: Details on the decomposition of the semielasticity of capital to monetary policy

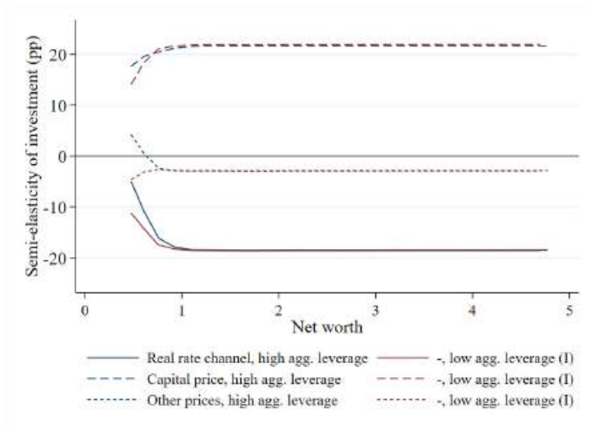
(a) Channel decomposition, low productivity firm



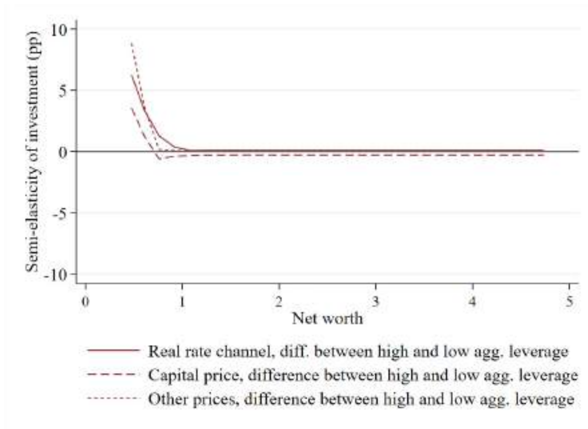
(b) Difference, low productivity firm



(c) Channel decomposition, high productivity firm



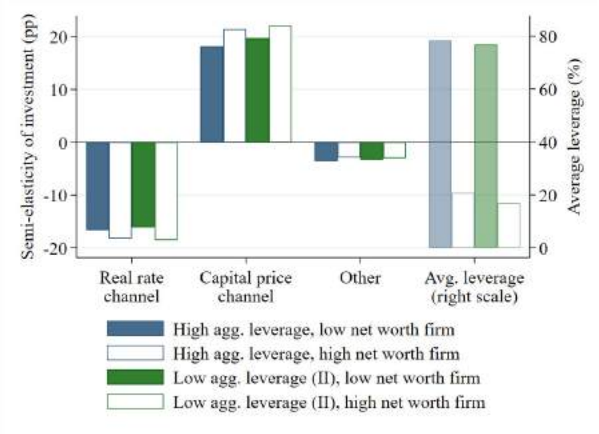
(d) Difference, high productivity firm



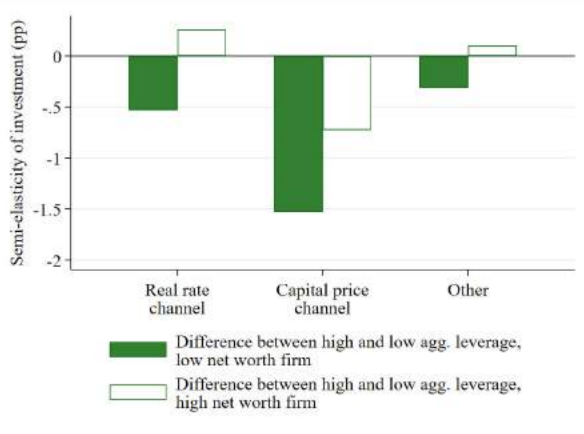
Notes: The semielasticity of capital with respect to a contractionary monetary policy is decomposed into three channels by feeding the response of one variable in the model while holding all other prices fixed. As opposed to Figure 6, we show here the full distribution of initial net worth and explicitly for two levels productivity z. Blue is the OW20 parameterization of the model, red represents responses from the alteration in which new-born firms start with higher initial capital, leading to a lower steady state aggregate leverage (46% vs. 49%). The right-hand panels show the differences between blue and red lines in the left-hand panels.

Figure C3: Decomposition of the semielasticity of capital to monetary policy

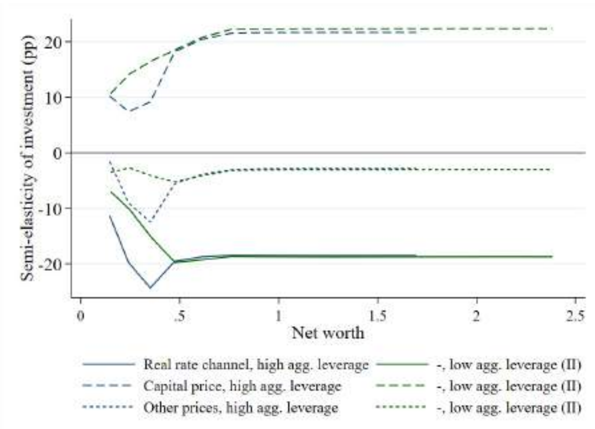
(a) Average firm leverage



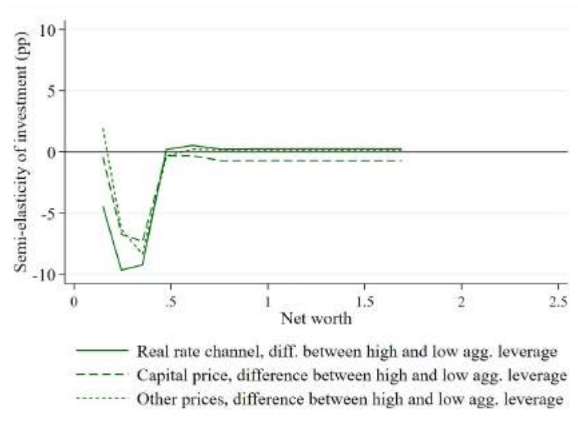
(b) Average firm spreads



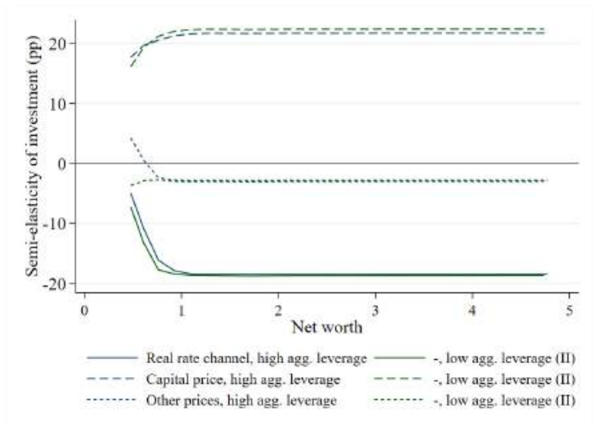
(c) Channel decomposition, low productivity firm



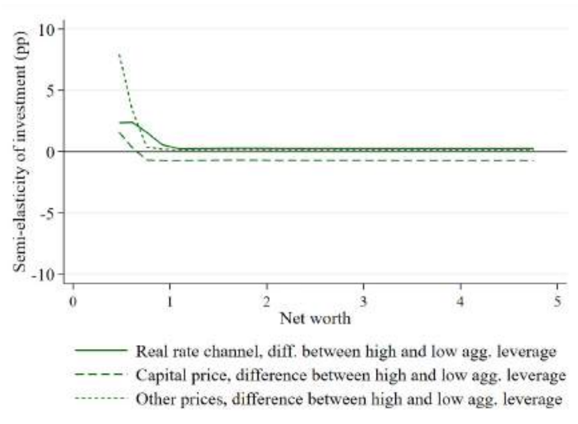
(d) Difference, low productivity firm



(e) Channel decomposition, high productivity firm



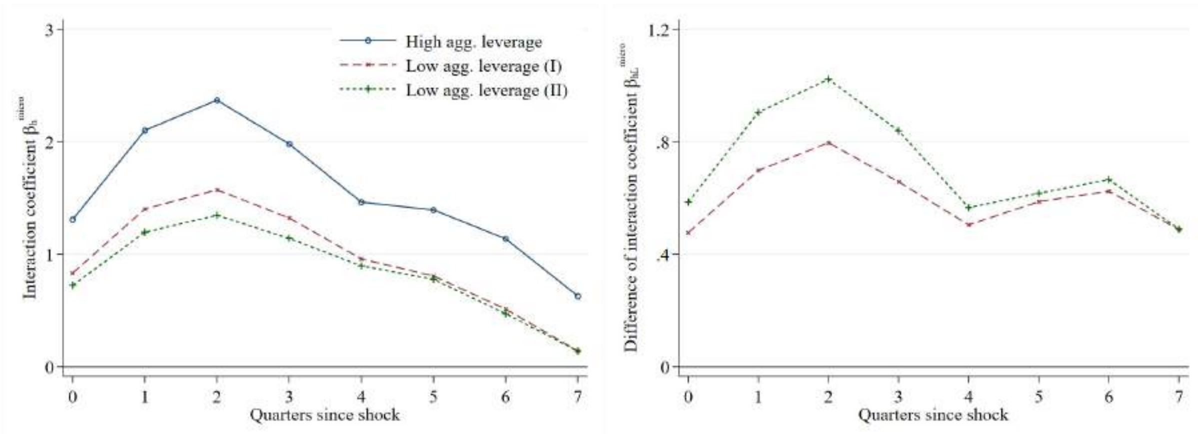
(f) Difference, high productivity firm



Notes: The semielasticity of capital with respect to a contractionary monetary policy is decomposed into three channels by feeding the response of one variable in the model while holding all other prices fixed. This charge is the analogue to Figure 6 and Figure C2 for the parameterization of the model where we generate lower aggregate leverage by reducing the exogenous exit probability.

Figure C4: State dependence of financial heterogeneity effects of monetary policy in the model

(a) Model-implied interaction coefficient (b) Difference



Notes: OW20 generate a panel of firms treated with innovations to the policy rule and subsequently estimate regression Equation (2) on the simulated data. The coefficients β_h^{micro} are positive, indicating that high-leverage firms decrease their investment less after a contractionary monetary policy shock. The results based on their parameterization are depicted with the solid blue line. We repeat the exercise separately for both our counterfactual where the initial distribution of leverage is lower (with a 46% average leverage instead of OW20's 49%). In both cases, the estimates for β_h^{micro} are still positive but smaller than in the baseline case. While high-leverage firms always respond less to monetary policy, this heterogeneity is particularly pronounced in times where many firms have high leverage. Panel (b) subtracts the blue lines from the dashed lines in Panel (a). See Figure 10 for the empirical counterpart of this difference.