Firms' Expected Growth and the Transmission of Monetary Policy to Investment*

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Abstract

This paper studies how firms' expected long-term growth affects the transmission of monetary policy to investment. Using analyst forecasts of long-term growth, we document that investment in high-growth firms is significantly more sensitive to monetary policy shocks. This effect persists even after accounting for heterogeneity in firms' exposure to financial frictions and is, in fact, stronger among firms with high liquidity and low leverage. We show that our main result is consistent with neoclassical models of investment, where long-term growth determines the duration of the firms' cash flows and thus their responses to interest rate changes.

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1 Introduction

How firms adjust investment following a monetary policy shock is a central question in macroeconomics. At the micro level, empirical evidence documents substantial cross-sectional heterogeneity in the response of firms' investment to changes in interest rates. Identifying the sources of this heterogeneity and their relative importance has been a central focus of the literature. One prominent view emphasizes financial frictions that affect firms' access to external finance, such as differences in leverage or liquidity (Ottonello and Winberry, 2020; Jeenas, 2025). Under this view, monetary policy influences investment not only through intertemporal discounting but also by tightening or relaxing financing constraints. A complementary perspective instead focuses on the heterogeneity in firms' real investment technologies, such as capital adjustment costs and time-to-build restrictions. These differences generate variation in the speed and the extent to which firms' investment can respond to changes in their cost of capital (Krusell et al., 2023; Fernandes and Rigato, 2025; Selgrad and Siani, 2025).

In this paper, we contribute to the latter view and study how firms' expected long-term growth affects the transmission of monetary policy to investment. Using financial statement data for publicly traded firms merged with analysts' forecasts, we find that differences in expected growth generate differential responses to monetary policy shocks. The differential responses we find are of similar magnitude to those attributed to financial frictions in the existing literature (e.g., Ottonello and Winberry, 2020; Jeenas, 2025), suggesting that differences in expected growth account for a comparable share of the cross-sectional variation in investment responses.

Conceptually, we argue that these responses operate through a simple valuation channel, rather than financing constraints. We show that our empirical finding is consistent with a textbook neoclassical model of investment, in which a firm's long-term growth is a key object for understanding the sensitivity of investment to the interest rate. In the model, there is a mapping between a firm's investment response to an interest rate shock and the duration of its cash flows. Intuitively, because high-duration firms have a more back-loaded path of future cash flows, their marginal value of capital, and thus their investment, is more sensitive to a change in the interest rate. In fact, partial-equilibrium interest rate semi-elasticity in the model is proportional to the duration, which in turn is pinned down by the long-term growth rate of the firm.

To test this mechanism in the data, our main empirical analysis estimates the relation between the interest rate semi-elasticity of investment and firms' long-term growth expectations. As is standard in the literature, we do so by using local projection methods (Jordà, 2005) and high-frequency monetary policy shocks to estimate the differential effect, sorting firms by growth expectations. In terms of measurement, we proxy for these expectations by using analysts' long-term growth forecasts of firms' earnings per share. Our baseline specifications include firm and sector-by-time fixed effects to capture permanent differences across firms and to isolate the partial-equilibrium response of investment, as in our framework. Crucially, we also control for other variables that have been shown to affect the transmission of monetary policy to investment, and that may be correlated with expected growth, such as proxies for financial frictions (e.g., liquidity and leverage). This allows us to distinguish our mechanism from the differential effect driven by financial frictions and focus on the relevance of real frictions in explaining heterogeneity across firms.

Our main finding is that high-growth firms are more sensitive to monetary policy. In particular, we show that a one standard deviation increase in the expected long-term growth of a firm increases its sensitivity to a 25 bps monetary policy shock by close to 2 percent at its peak. The effect is also persistent, with significant differences in the cumulative response of high and low growth firms 5 years after the shock. This finding is robust to a broad set of robustness tests, including different measures of expected growth, monetary policy shocks, sample definitions, and definitions of total capital, among others. Importantly, our result not only persists when controlling for the differential effect of firm characteristics deemed important by the literature, but it is also similar in magnitude, emphasizing the importance of our mechanism. Moreover, we show that the differential response of high-growth relative to low-growth firms is around half of the average effect of the shock, which makes long-term growth an important source of heterogeneity in the cross-section.

We also find that among high-growth firms, the reaction of intangible capital investment is slightly stronger and more persistent than physical capital. In particular, we break total investment by capital type (physical and intangible) and redo our baseline estimation. On the one hand, the response of physical capital plateaus at around 1.5 percent, three years after the shock, and then reverts towards the end of our estimation horizon. On the other hand, intangible capital exhibits a more pronounced response, with a peak estimate slightly larger than 2 percent, significant throughout our estimation horizon. Taken together, this pattern suggests that, for high-growth firms, intangible investment is more responsive to monetary policy, consistent with R&D—one of the main components of intangible capital—being a high-duration investment.[1]

In our theoretical framework, the interest rate semi-elasticity depends on the long-term growth rate through its dependence on the duration of the firm's cash flows. Therefore, we extend our baseline analysis to sort firms directly by their cash flow duration, using data on firms' discount rate from (Gormsen and Huber, 2025). While in our baseline analysis we focus on variation coming from different timing

[1] In fact, as we show in Section 3, NAICS sector 54, which includes R&D is the sector with higher duration.

of expected cash flows (i.e., growth rates), this approach allows us to incorporate variation in firms' cost of capital. We also use other measures of duration from the literature, such as a high-frequency identification of duration, using stock price changes around the shock, balance sheet measures of equity duration (Goncalves, 2021), and the inverse of the book-to-market ratio. We find estimates overall consistent with our main result, suggesting that heterogeneity in growth rates is the key source of variation in our mechanism.

Furthermore, we find that our mechanism is amplified by firms' financial conditions. That is, firms with high long-term growth expectations *and* high liquidity or low leverage cut investment even more aggressively in response to the shock, suggesting our main results are not driven by high-duration firms having less access to external finance. Put differently, even within the set of firms less likely to be constrained by financial frictions, there is a high response of high-duration firms to the shock. Therefore, the fact that our estimated elasticity is amplified emphasizes that even if high-growth firms are more exposed to financial constraints, it is the direct intertemporal discounting mechanism that plays a dominant role in explaining the main result of our paper.

Literature review. Our paper is related mainly to three strands of the literature. First, it relates to research studying the heterogeneity in firms' responses to monetary policy. Some recent examples focus on leverage (Ottonello and Winberry, 2020), size (Gertler and Gilchrist, 1994; Gnewuch and Zhang, 2025), age (Cloyne et al., 2023; Krusell et al., 2023), liquidity (Jeenas, 2025), debt maturity (Jungherr et al., 2024), cost of capital (Wroblewski, 2024), among others. While previous work has focused on financial frictions to explain the differences in sensitivities across firms, we offer a mechanism that highlights the importance of real frictions. In particular, we document a stronger response for high-growth firms, even after accounting for heterogeneity in exposure to financial frictions. Closest to us, Krusell et al. (2023) shows that firms' age is a key variable to understand variation in firm-level elasticities. While we do find an important role for age, our mechanism highlights that expected long-term growth—rather than age itself—is the key driver of heterogeneity in firm-level elasticities.

Second, we contribute to the literature studying the transmission of monetary policy to different types of investments (Döttling and Ratnovski, 2023; Dogan and Ozturk, 2024; Selgrad and Siani, 2025; Fernandes and Rigato, 2025). Recent work by Selgrad and Siani (2025) and Fernandes and Rigato (2025) show that when credit tightens, firms change the composition of their investment towards shorter-horizon projects. Similarly, Döttling and Ratnovski (2023) show that firms that are relatively more intensive in intangible capital present market value and investment that is less responsive to monetary policy shocks.[2] Relative to their work, we show that these results are consistent with differential responses due to heterogeneity in growth expectations. For example, even if intangible-intensive firms are on average less sensitive to monetary policy, among high-growth firms, intangible investment displays a relatively larger response than physical capital to the shock.

Third, our paper relates to the literature studying cash flow duration and its implications for firm outcomes (Weber, 2018; Kroen et al., 2021; Gormsen and Lazarus, 2023; Offner, 2025). For example, Kroen et al. (2021) find that lower interest rates lead to higher market concentration due to industry leaders having high duration relative to industry followers. Offner (2025) shows that growth stocks are significantly more sensitive to monetary policy than value stocks. Gormsen and Lazarus (2023), using our same long-term growth measure as a proxy for duration, document that this variable is a key determinant of the premium on short-duration firms. Moreover, our paper shares some of the intuitions discussed in Antràs (2023) and Antràs and Tubdenov (2025), as they hinge on the relative value of different decisions depending on the timing of the payoffs. We contribute to this literature by studying how duration affects firms' investment response to monetary policy, both in terms of aggregate investment and specific capital inputs.

Layout. The rest of the paper is organized as follows. Section 2 presents a standard neoclassical model of investment to illustrate the main mechanism behind our empirical analysis. Section 3 describes our data sources and the measurement of our main variables. Section 4 presents the results of our main empirical analysis. Section 5 concludes.

2 Stylized Framework

To illustrate how interest rate shocks generate a reallocation of investment from high-growth to low-growth firms, we present a textbook neoclassical model of investment and show that a firm's long-term growth is a key variable for the investment semi-elasticity to the interest rate. In that sense, the model provides guidance for our empirical exercise. In particular, we get an expression for the elasticity that directly maps to a firm's cash flow duration, which in turn depends on the long-run growth rate of the firm. We use this expression to motivate the specification we estimate in Section 4, where we use monetary policy shocks as a source of exogenous variation in interest rates and estimate the elasticity for high and low growth firms.

[2] As we will show below, cash flow duration can be expressed as the semi-elasticity of a firm's market value to a permanent change in the interest rate. Therefore, these results would suggest intangible-intensive firms have low duration and a smaller interest rate elasticity of investment, consistent with our mechanism. However, for this interpretation, we would need to make several assumptions to identify duration from high-frequency changes in stock prices around monetary announcements. We discuss these assumptions in footnote 28.

Time is continuous and indexed by $t \in \mathbb{R}_+$. There is an infinitely-lived representative firm that produces a single good, with price normalized to one, and that uses capital and labor as inputs for production. At every period, the firm hires labor frictionlessly at a wage w_t, which it takes as given.[3] However, to increase its capital stock by one unit, the firm must buy $1 + \Phi(I_t, K_t)$ units of capital at price $p_{K,t}$, with Φ strictly increasing and convex. Let $\Pi(K_t; w_t)$ be the firm's profit function after solving for the static labor demand decision, then the firm solves the following dynamic problem:

$$V(K_t) = \max_{(I_s)_{s\geq t}} \int_t^\infty e^{-\int_t^s r_u \mathrm{d}u} \left(\Pi(K_s; w_s) - p_{K,s}\left(I_s + \Phi(I_s, K_s)\right)\right) \mathrm{d}s, \tag{1}$$

$$\text{s.t. } \dot{K}_t = I_t - \delta K_t, \tag{2}$$

taking as given the initial capital stock K_0, as well as the path of input prices and the discount rate $(r_s)_{s\geq t}$, with δ denoting the depreciation rate of capital. The optimality conditions are given by:

$$p_{K,t}\left(1 + \Phi_I(I_t, K_t)\right) = q_t, \tag{3}$$

$$\Pi_K(K_t; w_t) - p_{K,t}\Phi_K(I_t, K_t) - q_t\delta = r_t q_t - \dot{q}_t, \tag{4}$$

$$\lim_{t\to\infty} e^{-\int_0^t r_u \mathrm{d}u} q_t K_t \leq 0, \tag{5}$$

where $q_t \equiv V'(K_t)$. Integrating Equation (4) forward and imposing the transversality condition, we get:

$$q_t = \int_t^\infty e^{-\int_t^s (r_u+\delta)\mathrm{d}u} \left(\Pi_K(K_s; w_s) - p_{K,s}\Phi_K(I_s, K_s)\right) \mathrm{d}s. \tag{6}$$

This is the standard result that the firm's marginal q is the present value of the future marginal product of capital, which consists of the additional output the firm creates $\Pi_K(K_t; w_t)$ and the reduction in future adjustment costs $p_{K,s}\Phi_K(I_t, K_t)$ it pays.

Suppose now that both the Π and Φ have constant returns to scale, that is, that

$$\Pi(K_t; w_t) = A(w_t)K_t, \tag{7}$$

$$\Phi(I_t, K_t) = \phi(i_t)K_t, \tag{8}$$

where $i_t \equiv I_t/K_t$. Define also $g_t \equiv i_t - \delta$, then we have a dynamic system of three equations, namely (2)-(4), and 3 unknowns (i_t, g_t, q_t), with boundary conditions given by K_0 and Equation (5). If we consider a balanced growth path where r_t, $p_{K,t}$ and w_t are constant, then Equation (6) pins down the long-run value

[3] We refer to labor as the only other input besides capital just for illustrative purposes. The results shown in this section can be easily extended to allow for multiple other inputs (intermediates, materials, etc) as long as we assume they can be solved as a static problem.

of q:

$$q = \frac{\Pi_K - p_K \Phi_K}{r+\delta} = \frac{A(w) - (i + \phi(i))p_K}{r-g}, \tag{9}$$

where Π_K, Φ_K are shorthand notation for the values of $\Pi_K(K_t; w)$, $\Phi_K(I_t, K_t)$ on the balanced growth path, and where the second equality follows from the constant returns to scale assumption on the profit and adjustment cost functions. If we do a perturbation to Equation (4) around the balanced growth path and integrate forward, we obtain:

$$\mathrm{d}\log q_t = (r+\delta)\int_t^\infty e^{-(r+\delta)(s-t)}\mathrm{d}\log\left(\Pi_{K,s} - p_{K,s}\Phi_{K,s}\right)\mathrm{d}s - \int_t^\infty e^{-(r+\delta)(s-t)}\mathrm{d}\log(r_s+\delta)\mathrm{d}s, \tag{10}$$

where we use shorthand notation $\Pi_{K,s} \equiv \Pi(K_s; w_s)$ and $\Phi_{K,s} = \Phi(I_s, K_s)$. This last equation can be seen as a generalization of Equation (9), valid not only on the baseline path, but also on any perturbed path around it. Intuitively, it shows that the change in the marginal value of capital can be decomposed into a cash flow effect, given by the expected change in the future marginal product of capital, and a discount rate effect given by expected changes in the future cost of capital.

From Equation (3), we know that the investment response to an interest rate change will depend on the response of the marginal value of capital to the same shock, which in turn depends on the two terms discussed above. However, using the functional form assumptions from Equations (7) and (8), we can express Equation (10) as:

$$\mathrm{d}\log q_t = \underbrace{(r-g)\int_t^\infty e^{-(r-g)(s-t)}\frac{A'(w)\mathrm{d}w_s - (i+\phi(i))\mathrm{d}p_{k,s}}{A(w) - (i+\phi(i))p_k}\mathrm{d}s}_{\text{Indirect GE effect on input prices}} - \underbrace{\int_t^\infty e^{-(r-g)(s-t)}\mathrm{d}r_s\mathrm{d}s}_{\text{Direct effect on valuation}}. \tag{11}$$

The equation above shows that for a small perturbation around the balanced growth path, the change in the marginal value of capital will depend on a direct effect that changes the net present value of future cash flows, and an indirect effect given by the equilibrium response of input prices.

From Equation (11), we can do comparative statics and get a sense of why we are interested in long-run growth rates when looking at the response of investment to an interest rate shock. For that matter, assume the following functional form for the adjustment cost:

$$\phi(i) = \frac{1}{\varphi}\exp(\varphi i) - i - \frac{1}{\varphi}, \tag{12}$$

with $\varphi > 0$ a parameter that captures the sensitivity of investment to the adjustment costs.[4] Then, from the firm's first-order condition, we have that

$$\frac{\mathrm{d}i}{\mathrm{d}r} = \frac{1}{\varphi}\frac{\mathrm{d}\log q}{\mathrm{d}r}. \tag{13}$$

This means that a firm's response to an interest rate shock will depend, through the effect of the shock on the marginal value of capital, on the direct and indirect effects discussed above. However, if we assume all firms produce using the same technology, including sector-by-time fixed effects allows us to isolate the partial equilibrium response of investment, which is proportional to duration.[5] That is, pre-shock cash flow duration, determined by g, is the relevant variable for understanding investment dynamics around an interest rate shock. To see this, assume the firm is on the balanced growth path and is hit by an unexpected shock of magnitude σ that mean reverts at rate ρ with perfect foresight, that is, $r(t) = r + \sigma \exp(-\rho t)$. The *partial equilibrium* response of investment to this shock, up to a first order, is given by:

$$\frac{\mathrm{d}i_t}{\mathrm{d}r_t} = -\frac{1}{\varphi}\frac{1}{r-g+\rho}, \tag{14}$$

where the last term converges to the firm's duration before the shock as we approach the limiting case of a permanent shock to the interest rate (i.e., as $\rho \to 0$).

Equation (14) shows why our paper focuses on expected long-term growth as a key variable for understanding differential effects of monetary policy. In this simple model, investment in firms with higher growth on the balanced growth path (i.e., higher duration) is more sensitive to changes in interest rate due to a higher valuation effect. Importantly, we show that it is g and not necessarily δ what governs this elasticity, as firms with similar depreciation rates may differ on how "fast" they can scale up their capital (pinned down by φ).[6]

Although this model formalizes the role of g in the investment response, the elasticity is constructed as a first-order perturbation around the balanced growth path, which is not the case in the data. Further, the representative firm framework abstracts from the rich heterogeneity in expected growth we see in analyst forecasts. In fact, the effect we estimate in the empirical section uses precisely the variation,

[4]Note that $\Phi(\cdot)$ satisfies the standard assumptions for this class of models, that is, $\Phi(I,K) > 0$, $\Phi_K(I,K) < 0$, $\Phi_{II}(I,K) > 0$ and $\Phi(0,K) = \Phi_I(0,K) = 0$.

[5]Previous work has used the depreciation rate as a proxy for the duration of the marginal investment (De Fraisse, 2023; Wroblewski, 2024). Under our model, using δ, as opposed to cash flow duration, could generate measurement error that would bias the results to 0. In fact, in Section 4 we show that the interest rate elasticity is significantly larger once we use our proxy for cash flow duration, as opposed to using the depreciation rate as a measure of *asset* duration.

[6]The parameter φ can have many interpretations. For example, physical adjustment costs, time-to-build, customer base acquisition, among others.

across firms and over time, in the expected growth rate, instead of a constant balanced growth path. In the data, we have analysts' expectations over a horizon of 3-5 years, where the analysts are asked to report their forecast over the "next full business cycle". We choose the representative framework in the main body as it is more parsimonious and allows us to illustrate our mechanism more clearly. Nevertheless, in Appendix A we generalize the model to a case where firms are heterogeneous in their growth rates due to life-cycle dynamics, which is one way to generate an investment elasticity that reflects the heterogeneity in expected growth seen in the data.[7]

3 Data and Measurement

In this section, we describe our main sources of data, the cleaning procedure, and the sample selection used in our empirical analysis. For our main results, we construct a panel of publicly traded firms by combining information from financial statements and analyst forecasts. We then merge this data with identified monetary policy shocks and standard macroeconomic aggregates.

3.1 Data sources and Sample Selection

Compustat. Our main source of firm-level data comes from quarterly Compustat (provided through WRDS). This is a panel that covers all U.S. publicly traded firms and offers rich detail on firms' financial statements. We use this dataset to construct series for physical and intangible capital, as well as standard financial variables. As in most of the literature, we construct capital series by using the perpetual-inventory method (PIM). For intangible capital, we follow Peters and Taylor (2017), take an initial value of intangible stock, and then use research and development (R&D) expenditures and selling, general, and administrative (SG&A) costs to construct its evolution over time. The construction of both series is described in greater depth in Section 3.2. For standard financial variables, see Appendix B for details on variable definitions. We winsorize all variables (except firm age) at the top/bottom 0.5 percent of the distribution to make sure our results are not driven by outliers.

Analyst Forecasts We use IBES as the source for analyst forecasts. This dataset offers a comprehensive coverage of U.S. publicly traded firms by surveying analysts on their forecast for different financial variables over a range of horizons. We focus on the median long-term growth (LTG) forecast of firms' earnings-per-share (EPS).[8] This variable forecasts firms' expected increase over the next full business

[7]There are several other ways to introduce heterogeneity in firms' growth rates. We choose to define two types of firms, "newborns" and "mature" with different growth rates, and an exogenous transition from newborn to mature (with the latter being an absorbing state) simply for analytical tractability.

[8]We winsorize analyst forecasts at the top/bottom 1 percent to clean for outliers and misreporting.

cycle. We take the median forecast as the "consensus forecast", as it is used more frequently in the literature, and it is not exposed to outliers. However, all our results hold when using the mean forecast. We also consider the latest consensus forecast in a given quarter as the forecast for that firm (Shore, 2024).

Monetary policy shocks. We use high-frequency monetary policy shocks, identified around FOMC announcements. We take the series from Bauer and Swanson (2023), which calculates the first principal component of the first four quarterly Eurodollar futures contracts, ED1–ED4. The responses are computed around a 30-minute window around the FOMC announcement using changes in yields 10 minutes before and 20 minutes after the announcement. We also exclude unscheduled FOMC announcements as they are more likely to provide private information about the state of the economy.[9] Given that this shock is unitless, we rescale it so that a one-unit change in the principal component corresponds to a one percentage point change in the ED4 rate.

These shocks are aggregated at the quarterly level, correcting by the timing of the announcement within the quarter (Ottonello and Winberry, 2020). In particular, the quarterly shock is computed as

$$\varepsilon_t^{\mathrm{mp}} = \sum_{\tau \in \mathcal{Q}(t)} \psi(\tau)\varepsilon_\tau^{\mathrm{mp}} + \sum_{\tau \in \mathcal{Q}(t-1)} (1 - \psi(\tau))\varepsilon_\tau^{\mathrm{mp}}, \tag{15}$$

where $\mathcal{Q}(t)$ is the set of days in quarter t and $\psi(\tau)$ is the remaining number of days in the quarter over the total number of days of that quarter. This means that we assign daily shocks entirely to that quarter if they occur on the first day of the quarter, but otherwise, we partially assign the shock between the current and subsequent quarter. For example, for a daily shock that happens on the last day of the quarter (i.e., $\psi(\tau) \approx 0$), the shock is almost entirely assigned to the next quarter.[10] Table 1 presents summary statistics of the high-frequency shocks and the series aggregated at the quarterly level. Figure C.1 depicts the time series for our baseline aggregation of the shocks.

[9] However, for our baseline period of analysis, most of the monetary policy decisions have been made during scheduled meetings.

[10] The intuition for this baseline aggregation is that we weight shocks across quarters, considering the amount of time agents had to respond. We also present results using the sum of the shocks within each quarter and show that our results remain unchanged.

Table 1: Summary Statistics of Monetary Policy Shocks

	High Frequency	Weighted	Sum
Mean	0.12	0.21	0.24
Median	0.07	-0.64	0.05
SD	5.29	5.28	6.36
P10	-6.67	-5.61	-8.13
P90	6.39	7.36	7.93
N	208	104	104

Notes: This table reports summary statistics of the monetary policy shocks used in our empirical analysis. These shocks are reported over our baseline sample 1994Q1-2019Q4. All variables are reported in basis points. The first column reports High Frequency shocks from Bauer and Swanson (2023), excluding unscheduled FOMC meetings and rescaled so that a unit shock corresponds to a one percentage point change in the ED4 yield. The second column aggregates to the quarterly level following Equation (15). The third column aggregates by summing shocks within each quarter.

Other Sources of Data The remaining sources of data are also standard. We directly download aggregate data from FRED to construct real series. In particular, we use the CPI index (`CPIAUCSL`) for all nominal variables except for investment, for which we use the investment price deflator (`IPDNBS`). We get industry-level depreciation rates from the Fixed Asset tables of the Bureau of Economic Analysis (BEA) and firm age from Jay Ritter's website.

Baseline sample. Our baseline time period is 1994Q1-2019Q4. We chose this period for two main reasons. First, due to the fact that FOMC announcements started being communicated directly through press releases in 1994, and second, to exclude the Covid shock.

At the firm-level, we follow standard practices in the literature to select our sample and to clean for potential misreporting and outliers. In particular, we exclude firms in finance, insurance, and real estate (FIRE), utilities and public administration, firms with negative assets, R&D expenditures, SG&A expenses or capital stock, acquisitions over 5 percent of total assets, investment rates at the top/bottom 0.5 percent, investment spells shorter than 40 quarters, and outliers in liquidity, leverage, sales, and R&D (as a share of total assets). See Appendix B.2 for details. Table 2 reports summary statistics of the main variables used in our empirical analysis.

Table 2: Summary Statistics of Firm-Level Variables

	N	Mean	Median	SD	P10	P90
Total Capital growth	290,698	1.47	0.69	4.69	-2.07	5.93
Physical Capital growth	318,730	0.64	-0.36	9.15	-5.59	7.54
Intangible Capital growth	284,024	2.01	1.24	4.27	-1.80	6.33
LTG	123,375	16.45	15.00	9.59	7.70	27.50
$\widehat{\text{LTG}}$	241,228	15.57	15.79	4.04	10.08	20.72
Age	367,547	22.81	18.00	19.35	5.00	43.00
Leverage	343,031	26.19	19.34	31.98	0.00	57.69
Total Assets	343,779	1,446.97	109.24	8,052.37	4.37	2,329.07
Tobin's Q	244,708	2.66	1.82	2.67	0.84	5.29
Liquidity	343,031	18.61	9.04	22.56	0.71	53.21
Sales growth	328,815	1.25	1.46	21.42	-21.15	23.13

Notes: This table reports summary statistics for the main variables in our sample. For more details on the sample selection and construction of those variables, please refer to Appendix B. Total, physical, and intangible capital growth are expressed in log-points times 100, while LTG, $\widehat{\text{LTG}}$, leverage ratio, liquidity, and sales growth are expressed in percentage points.

3.2 Constructing Total Capital Stock

Given that we are interested in how expected long-term growth matters for the response of a firm's investment to monetary policy, it is important that we extend our focus beyond just physical capital, as investment in different types of capital, with different expected cash flow timings, may be more/less sensitive to monetary policy. However, unlike physical capital, the measurement of intangible capital and innovation expenditures is typically more challenging, as it is not directly reflected in firms' balance sheets. To address this issue, we follow Peters and Taylor (2017) and construct intangible capital as a combination of R&D expenditures, organizational capital, and a depreciation rate. We combine all of them using the perpetual inventory method to construct series for intangible capital. Then, we define a firm's total capital as the sum of physical and intangible capital

$$K_{it}^{\text{Tot}} = K_{it}^{\text{Phy}} + K_{it}^{\text{Int}}, \tag{16}$$

where K_{it}^{Phy} and K_{it}^{Int} denote physical and intangible capital for firm i in period t and are constructed using the perpetual-inventory method. In particular, given an initial pair $(K_{i0}^{\text{Phy}}, K_{i0}^{Int})$ and a sequence of investments in physical and intangible capital, I_{it} and X_{it} respectively, both capital types are given by

$$K_{it}^{\text{Phy}} = (1-\delta_k)K_{it}^{\text{Phy}} + I_{it} \tag{17}$$

$$K_{it}^{\text{Int}} = (1-\delta_x)K_{it}^{\text{Int}} + X_{it}, \tag{18}$$

where δ_k is the depreciation rate of physical capital, and δ_x is the depreciation rate of intangible capital. For physical capital, we initialize K_{i0}^{Phy} using the earliest value of gross property, plant and equipment (variable `ppegtq`) as it has greater coverage, and then compute investment as changes in net property, plant and equipment (variable `ppentq`).[11] For intangible capital, we follow Benigno and Fornaro (2018) and initialize K_{i0}^{Int} at the initial investment flow over the depreciation rate, and consider as intangible investment the sum of R&D expenditures (variable `xrdq`) and 30% of SG&A expenses.[12,13] We interpret this share of SG&A spending as investment in organizational capital, including customer relations, human capital, brand, among others (Peters and Taylor, 2017). We then directly construct the series for intangible investment using this initial stock, the sequence of intangible investments, and a constant depreciation rate of 15 percent (yearly).[14]

3.3 Measuring Firm's Expected Long-Term Growth

In our framework, the interest rate semi-elasticity of investment depends directly on the firm's long term growth. Therefore, in this section we describe how we measure this object in the data. Concretely, we follow Gormsen and Lazarus (2023) and use the median analysts' long-term growth expectations on firms' earnings per share. This variable represents "consensus" forecast among analysts on the firms over the next full "business cycle", which refers to periods of three to five years. We argue this is a reasonable proxy as it captures persistent fluctuations in the firms' growth potential, as opposed to short-term forecasts that instead capture mainly short-term mean reversion of earning growth (Bordalo et al., 2024). Furthermore, as in Gormsen and Lazarus (2023), we do not directly use LTG forecasts but instead project this on firm observables:

$$\text{LTG}_{it} = \Gamma' \mathbf{X}_{it} + \epsilon_{it}, \tag{19}$$

where LTG_{it} is the median expected long-term growth for firm i at time t, and $\mathbf{X}_{it}$ is a vector containing the firm characteristics at time t, and ϵ_{it} is the error term, clustered at the firm and date level. We transformed all firm characteristics into cross-sectional percentiles, and therefore we are implicitly also

[11] We initialize the capital stock using gross PPE following Ottonello and Winberry (2020), as it has significantly more coverage.

[12] We also estimated our results initializing intangible capital at zero and the qualitative results remain unchanged. Although the initial capital stock does not affect the sensitivity of firms at the early part of our sample, it does matter for firms entering Compustat close to or after our initial sample period for our regression analysis.

[13] Compustat does not have an individual variable for SG&A, but can be constructed using variable `xsgaq` minus `xrdq` minus `rdipq`. We proceed as in Peters and Taylor (2017) and leave `xsgaq` unchanged whenever `xrdq` exceeds `xsgaq` but is less than `cogsq` or as zero when `xsgaq` is missing.

[14] This is the same depreciation rate used in Benigno and Fornaro (2018)

including time fixed effects.[15] These characteristics are book-to-market, operating income over market equity, asset growth, the payout ratio, and the firm's beta. We then consider the predicted values $\widehat{\text{LTG}}_{it}$ as our baseline for expected long-term growth.

Table D.1 presents the results of estimating Equation (19).[16] We consider Column (1) as our baseline specification, where we weight observations by the number of analysts, though our results are nearly identical when weighting by market equity or when running an unweighted regression.[17] As expected, high expected LTG is associated with lower book-to-market, operating income over market equity, and payout ratio, and negatively associated with asset growth and the firm's beta. The results are also all significant at the 99 percent level.

We use projected values of long-term growth instead of the actual consensus forecasts for mainly three reasons. First, analysts' forecasts may be biased due to sentiments or incentives (e.g., investment-banking relationships). Second, analyst expectations may themselves influence firm behavior, creating a potential reverse-causality bias. Third, because not all firms have analysts, this method allows us to increase our coverage and to avoid biasing our results due to the selection of analysts into firms. We do, however, show that our main results still hold when using raw data on LTG.

Figure 1 shows descriptive statistics of our estimated proxy of long-term growth. Panel (A) shows the cross-sectional distribution of $\widehat{\text{LTG}}$, while Panel (B) depicts time series for the average long-term growth estimate (weighted by market equity). We see rich heterogeneity in LTG forecasts, ranging from less than 5 percent to close to 30 percent. Further, when we look at the evolution over time, we see a big spike at the late 1990s/early 2000s, a significant decline prior to the Great Recession, and a somewhat persistent increase afterwards.

Figure 2 presents binned scatter plots, residualized by sector-time fixed effects (3-digit NAICS), to look at the correlation of $\widehat{\text{LTG}}$ with previous variables the literature has deemed important in the transmission of monetary policy to investment. Panels (A) and (B) show that high-growth firms are associated with higher liquidity and lower leverage ratios, suggesting these firms are less likely to be financially constrained. This is not obvious, as in principle, analysts could expect financially constrained firms to have high long-run growth if they think their constraints will become less binding over time (e.g., due to self-financing). Panel (C) also shows that high-growth firms are also smaller, which is

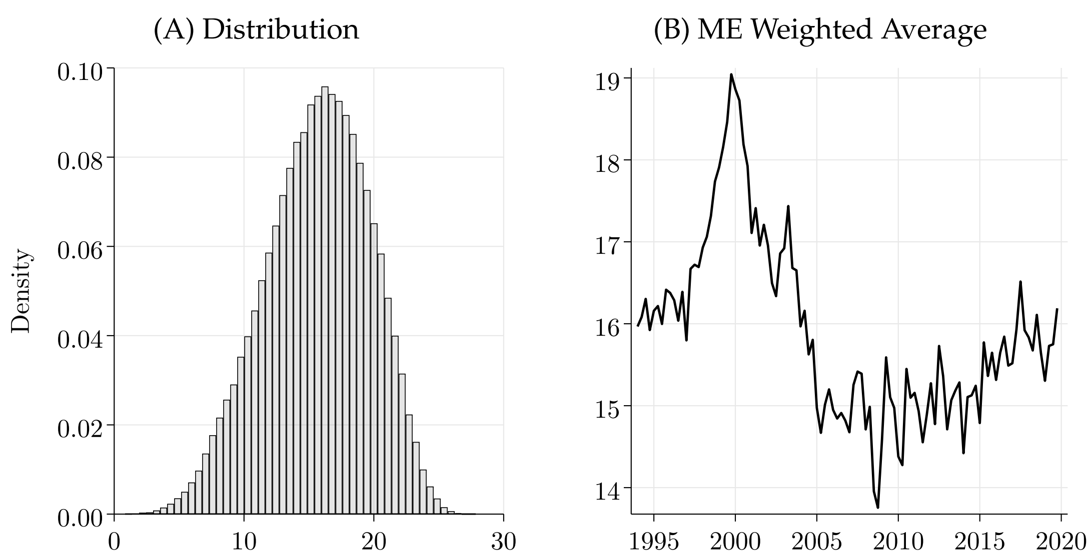
[15]This is the same regression estimated Gormsen and Lazarus (2023), though they also show that results look similar when also including firm fixed-effects.

[16]Table D.2 shows the same results but using the average instead of the median forecast as the consensus forecast.

[17]We choose this as our baseline regression mainly to keep our measure as close as possible to Gormsen and Lazarus (2023), even though weighting by market equity produces a higher R^2. Nevertheless, our results are not affected by this decision.

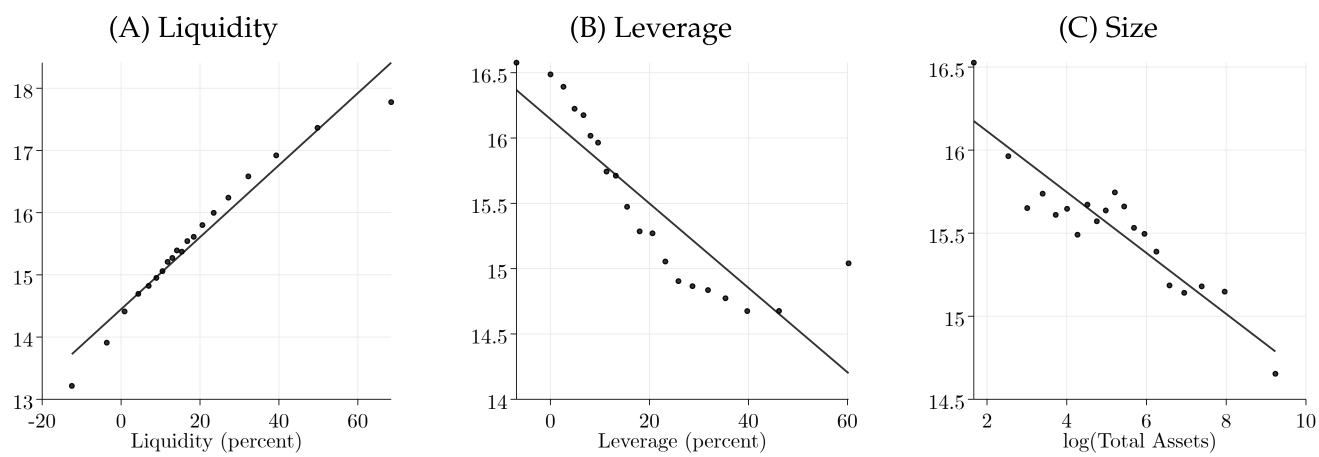
consistent with firm life-cycle dynamics.[18]

Figure 1: Distribution of $\widehat{\text{LTG}}$ and its Evolution Over Time



Notes: This figure presents descriptive statistics of our measure of expected long-term growth $\widehat{\text{LTG}}$. Panel (A) plots the cross-sectional distribution while Panel (B) plots the average $\widehat{\text{LTG}}$ over time, weighting by real market equity.

Figure 2: Determinants of $\widehat{\text{LTG}}$ at the Firm-Level



Notes: This figure presents binned scatter plots of the correlation of $\widehat{\text{LTG}}$ and firm observables. All figures control for sector-by-time fixed effects (3-digit NAICS).

3.4 A Simple Mapping From LTG to Duration

In this section, we present a simple mapping from expected long-term growth, which describes analyst expectations over the firms' path of future cash flows, into cash flow duration. This is defined as the

[18] We also find that high-growth firms are younger, though because the measurement of age in Compustat is less precise, we decided not to include it, but we can share this upon request. See Appendix B.1 for details on how we measure age.

value-weighted time to maturity of expected cash flows (Macaulay, 1938), or the semi-elasticity of the firm's market equity to the discount rate. Given this definition, consider an asset whose cash flows $(CF_t)_{t\geq 0}$ grow at some constant growth rate $g < r$, then $\mathbb{E}_0[\text{CF}_t] = \exp(gt)\text{CF}_0$. The value of this asset is given by:

$$V_0 = \mathbb{E}_0\left[\int_0^\infty \exp(-rt)\text{CF}_t \text{d}t\right] = \mathbb{E}_0\left[\int_0^\infty \exp(-(r-g)t)\text{d}t\right]\text{CF}_0 = \frac{\text{CF}_0}{r-g}, \tag{20}$$

which is the standard Gordon growth formula for asset prices. Therefore, using the definition of duration implies:

$$\mathcal{D} \equiv \frac{\mathbb{E}_0\left[\int_0^\infty t\exp(-rt)\text{CF}_t\text{d}t\right]}{\mathbb{E}_0\left[\int_0^\infty \exp(-rt)\text{CF}_t\text{d}t\right]} = -\frac{\partial \log V_0}{\partial r} = \frac{1}{r-g}, \tag{21}$$

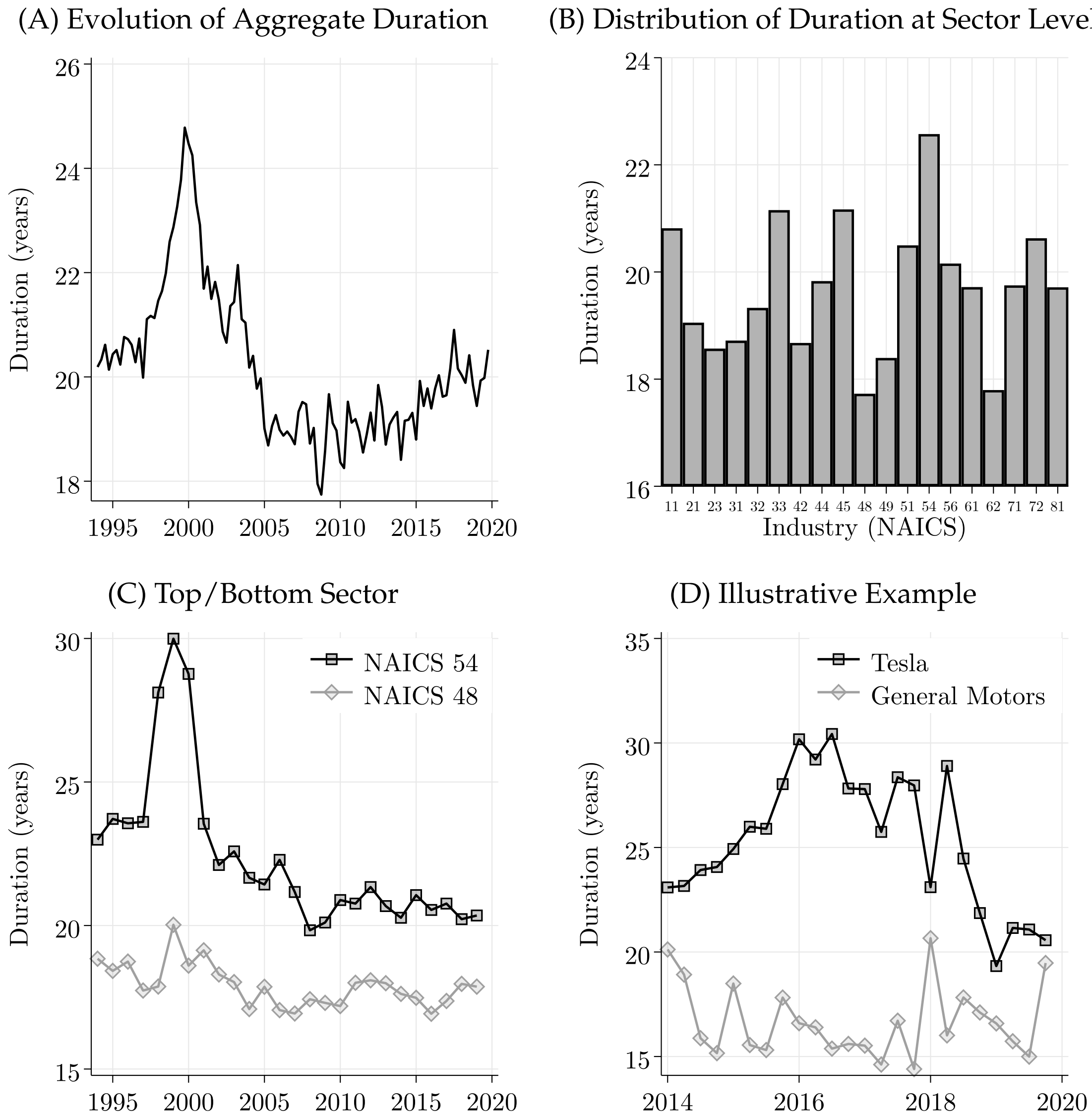
which is exactly the expression we got in Equation (14) when the shock is permanent (i.e., when $\rho \to 0$). From our sample of analyst expectations, we have estimates at the firm-quarter level of g, which, combined with the firm's discount rate, would allow us to directly impute the firm's cash flow duration over time. However, in our main empirical analysis, we focus on growth rates for mainly two reasons. First, it is hard to directly observe firms' discount rates in the cross-section and over time, making it difficult to accurately estimate our baseline regressions. Second, due to the fact that we are interested in variation in the timing of cash flows (i.e., growth rates), rather than variation on discount rates, as in Gormsen and Lazarus (2023). Nevertheless, in Section 4.4 we show that approximating duration with the Gordon formula, and predicted hurdle rates from Gormsen and Huber (2025), yields to consistent results.

To see how long-term growth maps into cash flow duration in our data, we do the following back-of-the-envelope calculation. We aggregate the data either at the industry or economy-wide level, weighting firms by market equity, and use Equation (21) to construct aggregate duration. That is, we compute the average g at the aggregate or sector-level and look at the implied cash flow duration. For that, we annualize $\widehat{\text{LTG}}$ as an estimate of g and assume $r = 0.1$, which is roughly the annual return of the S&P index over our sample period. Figure 3 depicts aggregate trends on this object. Panel (A) depicts the evolution of aggregate duration over time, where we see a big spike in the late 1990s/early 2000s, consistent with the variation shown for $\widehat{\text{LTG}}$ in Figure 1. Panel (B) shows duration across 2-digit NAICS sectors, while Panel (C) plots the time series of the two sectors that stand out: Professional, Scientific, and Technical Services (NAICS 54) and Transportation and Warehousing (NAICS 48). The former shows an average duration of roughly 23 years, while the latter of less than 18 years, a difference somewhat consistent over time. In addition, Panel (D) plots the evolution of duration of Tesla and General Motors, as an example of two firms with high and low duration, respectively (Dechow et al., 2021).[19]

Panels (B) through (D) present examples that we think are at the heart of our mechanism. First, Panels (B) and (C) show that the sector with the largest cash flow duration is the one that contains R&D, marketing and management consulting services, advertising, among others. This suggests that what we consider as intangible investments is associated with high duration. Similarly, Panel (D) highlights our main source of variation within industries, as the two firms operate in the same industry and have substantially different durations. In particular, in our main empirical analysis, we will test whether both firms respond differently to monetary policy in terms of their aggregate investment and their specific investment compositions.

[19]It is reassuring that we get somewhat similar estimates to Dechow et al. (2021) on the duration of both firms even though we use different methods and assumptions. In particular, they estimate an equity duration of 17.1 years for General Motors and 32 years for Tesla. Unlike us, their methodology follows Dechow et al. (2004), which estimates duration by forecasting future cash flows using accounting proxies and assumptions over their evolution over time.

Figure 3: Aggregate Trends in Duration



Notes: This figure presents descriptive statistics on our estimate of duration, given by Equation (21), using $r = 0.1$ (average return of S&P over our sample) and annualized $\widehat{\text{LTG}}$ as an estimate for g. These forecasts are made over a period of 3-5 years, and we annualized them by assuming a horizon of 3 years. Panel (A) depicts the time series for the average duration over our sample. Panel (B) reports the average duration across the different 2-digit NAICS sectors. Panel (C) follows the top/bottom sector from Panel (B) over time. These three panels present averages weighted by real market equity. Panel (D) plots the evolution of duration for Tesla and General Motors as an illustrative example.

4 Empirical Analysis

In this section, we present our main empirical results. We want to study how different firms and different types of investments respond to monetary policy. Concretely, we want to test if this response is larger for firms with high expected long-term growth prior to the realization of the shock. For that, we will employ local projection methods (Jordà, 2005) to estimate both *average* impulse responses, and *differential* effects by $\widehat{\text{LTG}}$.

4.1 Average Effect of Monetary Policy

Before going to our main results, we start by estimating the average response of investment to a monetary policy shock in our data. This provides a benchmark against which we can compare the magnitudes of our differential effect. For that, we estimate

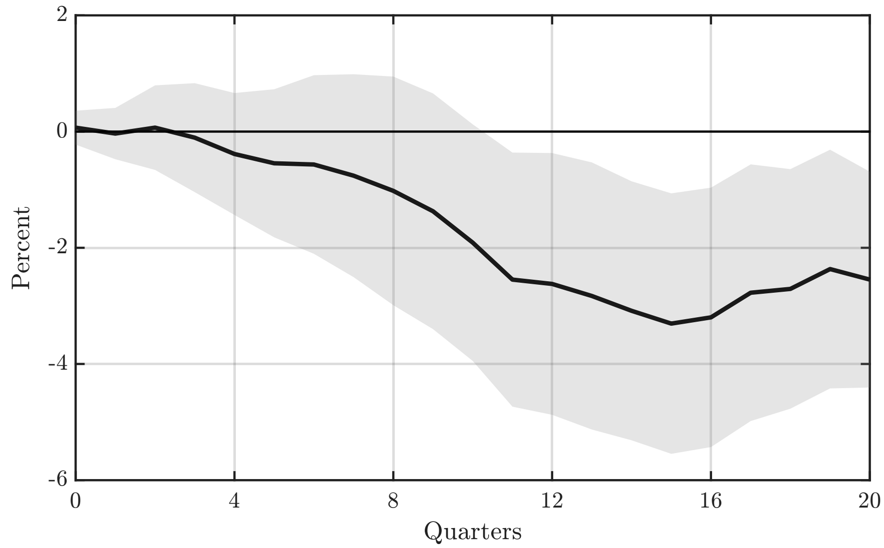
$$\log y_{it+h} - \log y_{it-1} = \alpha_i^h + \alpha_{sq}^h + \beta^h \varepsilon_t^{\text{mp}} + \Gamma' \mathbf{X}_{t-1} + e_{it+h}^h, \tag{22}$$

where $h \in 0, 1, \ldots, H$ denotes the horizon and $\log y_{it+h} - \log y_{it-1}$ denotes the long difference in the firm's capital over that horizon. The monetary policy shock is represented by $\varepsilon_t^{\text{mp}}$ and therefore our parameter of interest is β^h. In our baseline specification, we include firm fixed effects α_i, to control for time-invariant firm characteristics. We also include sector-fiscal quarter fixed effects α_{sq} as well as a set of idiosyncratic and aggregate controls $\mathbf{X}_{t-1}$. For the idiosyncratic controls, we include our measure of long-term growth $\widehat{LTG}$, log size (total assets), leverage, age, liquidity, Tobin's Q, and sales growth (year-over-year).[20] For aggregate controls, we include GDP growth, inflation, and the fed funds rate (all lagged). All the firm-level controls are lagged (except age) so that they are not affected by the monetary policy shock. Standard errors are computed using the methodology from Driscoll and Kraay (1998) to account for potential serial correlation within a firm over time, as well as cross-sectional correlation.

Figure 4 presents the estimated impulse responses to a 25 bps contractionary shock. We find a cumulative decline in investment that reaches a peak of about 3.5 percent roughly four years after the shock and then gradually attenuates toward the end of the estimation horizon. The response is persistent and statistically significant at medium and long horizons, highlighting that the effects of monetary policy on investment unfold slowly over time.

[20]For age, we take the max between the age implied by the earliest date the firm is present in Compustat and the founding year from Jay Ritter's database. Leverage and liquidity ratios are defined as total liabilities over total assets and cash and short-term investments over total assets, respectively. We measure Tobin's Q as the market value of the firm over the book value of assets, where we define the market value of the firm as the sum of its market equity plus the book value of debt.

Figure 4: Average Effect of Monetary Policy on Investment



Notes: This figure presents estimates of β^h in Equation (22) at different horizons $h \in 1, 2, \ldots, 20$. Shaded areas represent 90% confidence intervals, constructed using heteroskedasticity and autocorrelation robust Driscoll-Kraay standard errors.

4.2 Differential Effect by Long-Term Growth

To study whether firms with *ex-ante* higher long-term growth expectations are more sensitive to monetary policy, we estimate the following local projection regression:

$$\log y_{it+h} - \log y_{it-1} = \alpha_i^h + \alpha_{st}^h + \beta^h(\varepsilon_t^m \widehat{\text{LTG}}_{it-1}) + \Gamma' \mathbf{X}_{it-1} + \zeta' \mathbf{Z}_{t-1} \widehat{\text{LTG}}_{it-1} + e_{it+h}^h, \tag{23}$$

where we use the same dependent variable and horizon as Section 4.1, but our parameter of interest β^h now represents the *differential* response of capital investment to a 25 bps tightening for high/low growth firms (i.e., high/low $\widehat{\text{LTG}}$). In particular, we rescale $\widehat{\text{LTG}}$ by its standard deviation (approximately 1 percent when annualized), to compare our estimates with previous results from the literature.

The regressions include firm α_i and sector-by-time α_{st} fixed effects, and therefore our estimates of the heterogeneous response to monetary policy come from variation within a sector. The vector $\mathbf{X}_{it-1}$ includes log size, leverage, liquidity, and age, as well as their interaction with the monetary policy shock. This is important to isolate the effect that comes from variation in the duration of the firmss cash flows, as we showed earlier that long-term growth is highly correlated with these variables, and there is ample evidence of them being important in understanding the heterogeneous effects of monetary policy.[21] In addition, $\mathbf{X}_{it-1}$ also include controls for $\widehat{\text{LTG}}_{it-1}$, sales growth, Tobin's Q and fiscal quarter dummies, while $\mathbf{Z}_{t-1}\widehat{\text{LTG}}_{it-1}$ includes the interaction of $\widehat{\text{LTG}}_{it-1}$ with GDP growth to control for differential cyclical

[21] See, e.g. Ottonello and Winberry (2020); Cloyne et al. (2023); Krusell et al. (2023); Gnewuch and Zhang (2025).

sensitivities of high/low growth firms. Lastly, standard errors are clustered by firm and industry-time.

Figure 5 presents the estimates from Equation (23), which characterize the differential response of total investment to a 25 bps contractionary monetary policy shock across firms with different long-term growth expectations. Firms with a one standard deviation higher $\widehat{\text{LTG}}$ experience a significantly larger decline in investment, with the differential response rising over the first 12 quarters before plateauing at close to 2 percent. This effect is also quite persistent, with significant differences spanning our entire estimation horizon. Moreover, the dynamics of the estimates mirror those of the average response documented in Figure 4, while displaying sizable differences between high-growth and low-growth firms, consistent with the predictions of our theoretical framework.

Importantly, these differences persist even after controlling for standard firm characteristics that have been shown to shape heterogeneous investment responses to monetary policy, including firm age, size, liquidity, and leverage. In terms of magnitude, the estimated differential response is economically meaningful: a one standard deviation increase in $\widehat{\text{LTG}}$ implies an investment response that is on the order of one-half of the average cumulative decline documented in the previous section. As such, variation in long-term growth expectations accounts for a substantial share of the cross-sectional heterogeneity in investment responses. The size of the estimated effects is comparable to those documented for other firm characteristics in related work (e.g., Ottonello and Winberry, 2020; Jeenas, 2025), suggesting that long-term growth expectations capture an economically relevant source of heterogeneity in investment responses.[22]

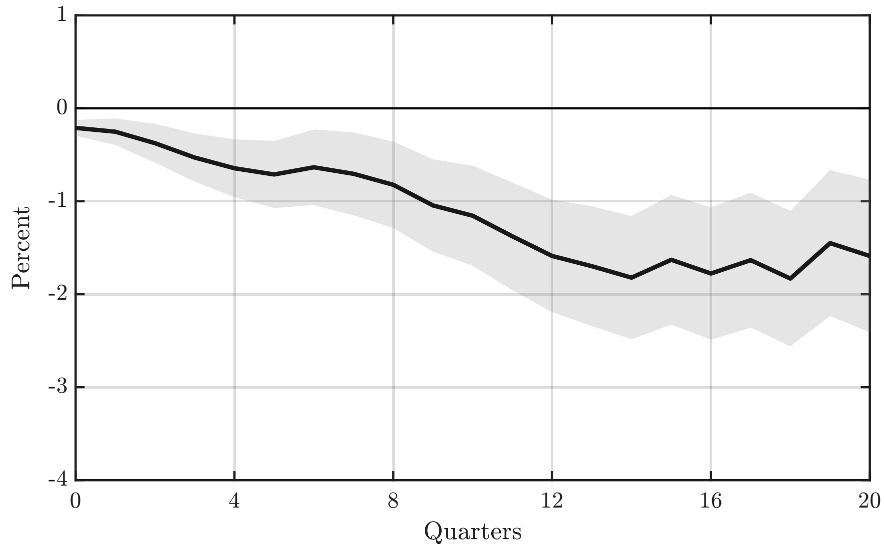
Investment responses to monetary policy may differ across capital types, reflecting for example differences in adjustment costs, depreciation rates, and the timing of expected payoffs. To explore this possibility, Figure 6 replicates the baseline specification in Equation (23) separately for physical and intangible capital. In both cases, firms with higher long-term growth expectations exhibit a larger decline in investment following a contractionary monetary policy shock. The differential response is however more pronounced and persistent for intangible capital, with effects that continue to build over time. By contrast, the response of physical capital is somewhat smaller and plateaus earlier and at a lower level.[23] Interestingly, this result contrasts with evidence of the *average* response of intangible investment being less sensitive to monetary policy shocks (Döttling and Ratnovski, 2023).

As we showed in our framework, cash flow duration is key for understanding the transmission of monetary policy to investment. In that sense, using the long-run expected growth of firms allows us

[22] Figure C.2 reports the coefficients for the other variables interacted with the shock. To make them comparable, estimates for liquidity, leverage size, and age are presented in terms of a one standard deviation shock.

[23] This pattern aligns with the observation that intangible-intensive sectors, for example, NAICS 54 (see Figure 3), are characterized by higher long-term growth expectations and thus longer implied duration.

Figure 5: Heterogeneous Response Conditional on Long-Term Growth Expectations



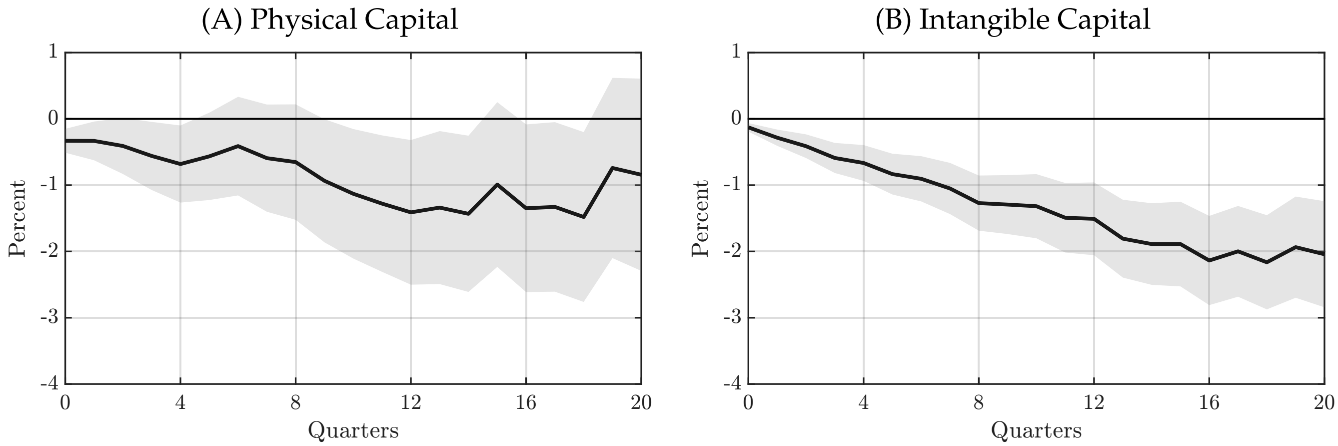
Notes: This figure presents estimates of β^h in Equation (23) at different horizons $h \in 1, 2, \ldots, 20$. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

to improve our measurement of the change in the marginal value of capital in response to the shock. In particular, previous estimates from the literature used the depreciation rate as a proxy for the duration of the firm's marginal investment (e.g., De Fraisse, 2023; Wroblewski, 2024), which may bias the interest rate elasticity of investment. This would understate the estimated elasticity by introducing classical measurement error, or if, for example, firms with high adjustment cost parameter φ also have low depreciation rates.

In this context, Figure 7 compares the estimated impulse responses of *physical* capital using our proxy of cash flow duration $\widehat{\text{LTG}}$ (as in Panel A of Figure 6) with the firm-average depreciation rate δ.[24] To make both estimates comparable, we use the negative of the depreciation rate and standardize it. We find that the estimated differential response of high-duration firms is significantly larger when using the analyst forecast of firms' long-term growth. In particular, a one standard deviation higher depreciation rate has a peak response of less than 0.5 percent, vanishing two years after the shock.[25] On the other hand, a one standard deviation higher expected growth rate has a peak effect of around 1.5 percent and is more persistent, with the effect being statistically significant almost 5 years after the shock. These differences are consistent with the intuition from the model that the response of investment not only depends on the depreciation rate, but also on their marginal product and on how fast firms can scale up capital (pinned down by the adjustment cost).

[24]We use physical capital, as opposed to total capital, as we use the firm-average depreciation rate of their physical capital.
[25]The magnitude and persistence found by us are consistent with the results in Wroblewski (2024).

Figure 6: Heterogeneous Response Across Capital Types



Notes: This figure presents estimates of β^h in Equation (23) at different horizons $h \in 1, 2, \ldots, 20$. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

4.3 Robustness

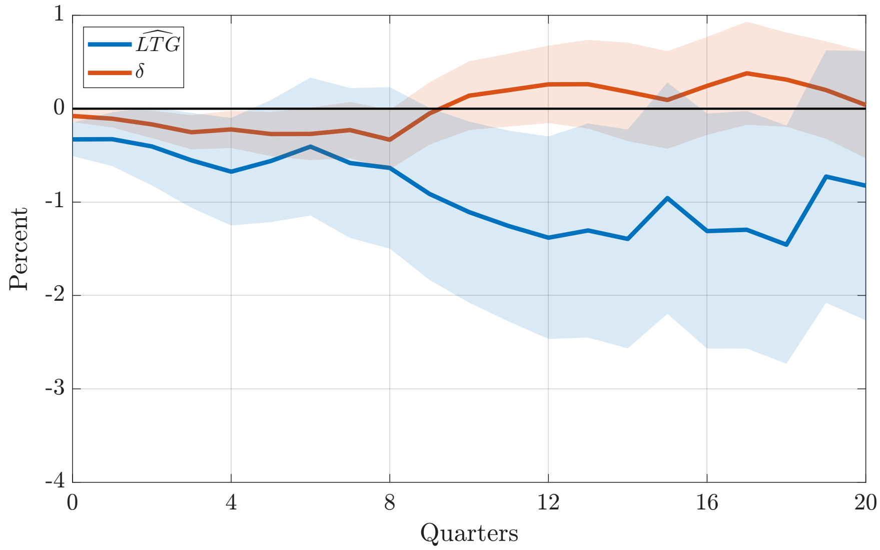
In this section, we provide a list of robustness exercises that suggest our results are not driven by the assumptions we made on the specification, sample and data cleaning process.

Raw Analyst Forecasts. In our main empirical analysis, we used projected long-term growth into observables due to potential endogeneity in analysts' forecasts. Here we show that our results hold when using the raw forecasts. Concretely, Figure C.3 presents the results of running Equation (23), but using the raw analyst forecasts instead of the projected ones. Even though we lose roughly half of our sample, results remain qualitatively identical to Figure 5. We choose however to use $\widehat{\text{LTG}}$ as our baseline as it increases our coverage and mitigates some of the risks associated with analyst forecasts (e.g., agency concerns and reverse causality).

Alternative Set of Controls for Differential Effect. In our baseline estimation, we included for a broad set of firm-level controls, as well as the interaction of many of these covariates with the monetary policy shock. The idea behind this is that long-term growth may be correlated with other variables known to generate heterogeneity in the response of investment to the shock, thus biasing our results. Here we show our results do not depend on which variables we include interacted with the monetary policy shock. Namely, Figure C.5 presents the estimates for the investment response two and four years after the shock. Our baseline estimates are nearly identical to alternative specifications, including no other regressors for the differential effect, or including only liquidity, leverage, size, and age separately (along with long-term growth).

Alternative Definitions. We check that our results do not depend on the different assumptions

Figure 7: Comparing the Differential Response by Asset and Cash Flow Duration



Notes: This figure presents estimates of β^h in Equation (23) for two separate specifications. The first uses $\widehat{\text{LTG}}$ as in Figure 5 (blue line), while the second uses the firm-average depreciation rate, computed as the average ratio of depreciation to net PPE from annual Compustat data (red line). We rescale the depreciation rate to minus the actual value so that both coefficients have the same sign. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

and definitions we made when estimating our baseline specification. First, we check that the results do not depend on what measure we use as the "consensus forecast" among analysts. Figure C.7 shows that our results are almost identical when using the average (as opposed to the median) forecast as the consensus. Next, we show our results hold when using a different aggregation of high-frequency shocks to quarterly frequency. In particular, Figure C.8 depicts similar qualitative and quantitative estimates. In addition, we rule out that our main result is not driven by the inclusion of "organizational capital" in our definition of intangible capital. Figure C.6 shows that our results remain unchanged when we do not capitalize any SG&A as organizational capital. In fact, if anything, we see a larger semi-elasticity.

Other Robustness Exercises. Finally, we perform other robustness tests to see that our results do not depend on the specification, high-frequency shocks, or time period employed in our main empirical analysis. First, we follow the specification in Ottonello and Winberry (2020) and use firm-level demeaned long-term growth (Figure C.9). Second, we use the shocks constructed by Jarociński and Karadi (2020), separating central bank information shocks (Figure C.10). Third, we estimate our baseline specification for the period pre-Great Recession and for our same time-period, but excluding the peak of the Great Recession, as in Nakamura and Steinsson (2018) and Meier and Reinelt (2024) (Figure C.11). Our results remain unchanged under this set of robustness tests.

4.4 Extensions

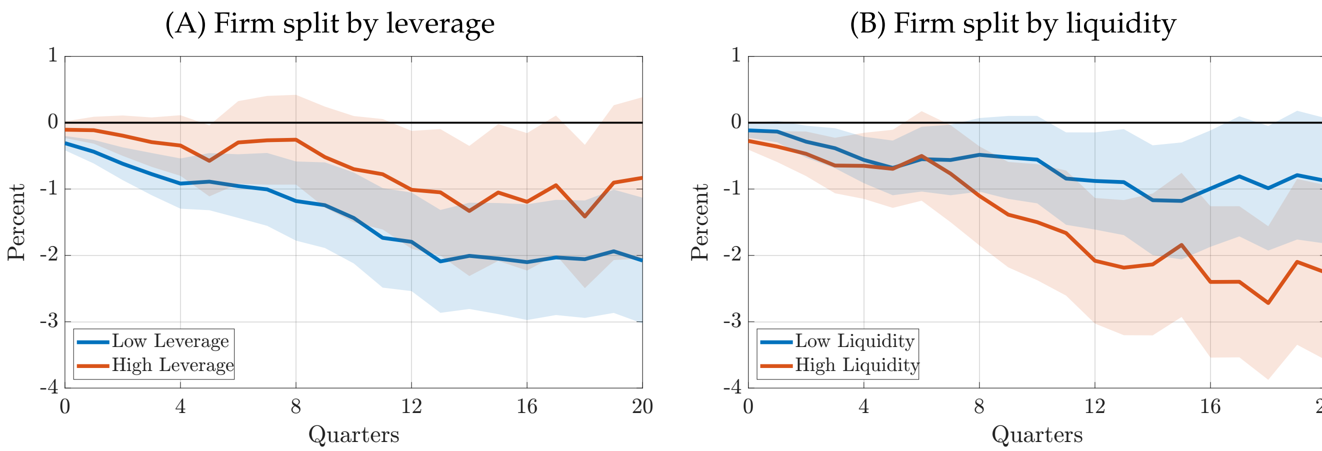
So far, both our model and empirical predictions have focused mainly on how the monetary transmission of investment to monetary policy depends on the growth rate of firms. We have argued that, due to their expected timing of cash flows, high-growth firms are more sensitive to changes in interest rates. We consider our results as an important first step in that direction, as we show that even after accounting for differential sensitivities to standard observables like leverage and liquidity, we still find that high duration firms respond more aggressively to monetary policy. In this section, we propose two additional exercises that allow us to validate our theoretical claims about growth affecting investment sensitivity, primarily through an intertemporal discounting channel. First, we split the sample of firms according to their liquidity holdings, and also by their leverage position, to see wether our result gets amplified in the sub-sample of firms that are less financially constrained. Second, we estimate our results using measures of cash flow duration, instead of just the expected growth rate.

Liquidity and Leverage Split. Even though our mechanism could be potentially amplified by other firm characteristics, for this exercise, we will study how our baseline effect depends on the firms' financial position, as there is substantial evidence documenting the effect of leverage and liquidity on firms' investment dynamics (e.g. Ottonello and Winberry, 2020; Jeenas, 2025). In that sense, consider the following example. Suppose there is an unexpected monetary easing. According to our results, high-growth firms would want to make large increases to their capital expenditures due to the increase in the net present value of every unit of investment. However, these firms may be disproportionately affected by their leverage or liquidity. For instance, banks may be less willing to extend credit to high-growth firms, as their elevated exposure to long-dated cash flows increases balance-sheet risk. Similarly, high-growth firms may invest relatively more intensively on investments hard to collateralize, like R&D, and thus depend more on internal resources to fund their investment.

To test this, we perform two cross-sectional splits of our data, first by leverage and then by liquidity. Namely, we take the firms' average leverage/liquidity and group them into high and low groups by doing a median split. Then, we estimate Equation (23) for each subsample. Figure 8 presents the results. There is one main result that stands out. Our baseline estimates are *amplified* for firms with low leverage or high liquidity, consistent with our previous intuition. This is particularly large for high liquidity firms, where the difference between high and low groups increases over the first 3 years, and then plateaus at a difference of over 1 percent. That is, firms with high duration *and* high liquidity reduce their investment by more than 1 percent more in response to a 25 bps shock.

Interestingly, the fact that the amplification is particularly pronounced for high-liquidity firms suggests that our main results cannot be attributed to high-growth firms having less access to external finance. Instead, it reinforces the interpretation that duration itself—rather than financing constraints—plays a central role in shaping the investment response to monetary policy.[26] Given this, we see our baseline estimates as a conservative lower bound of the true effect.

Figure 8: Heterogeneous Response by Leverage and Liquidity



Notes: Panel (A) of this figure presents estimates of β^h in Equation (23) for a high and low leverage sample. The high (low) leverage sample represents firms with average leverage above (below) the median. Panel (B) presents the results for a high and low liquidity sample. The high (low) liquidity sample represents firms with liquidity leverage above (below) the median. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

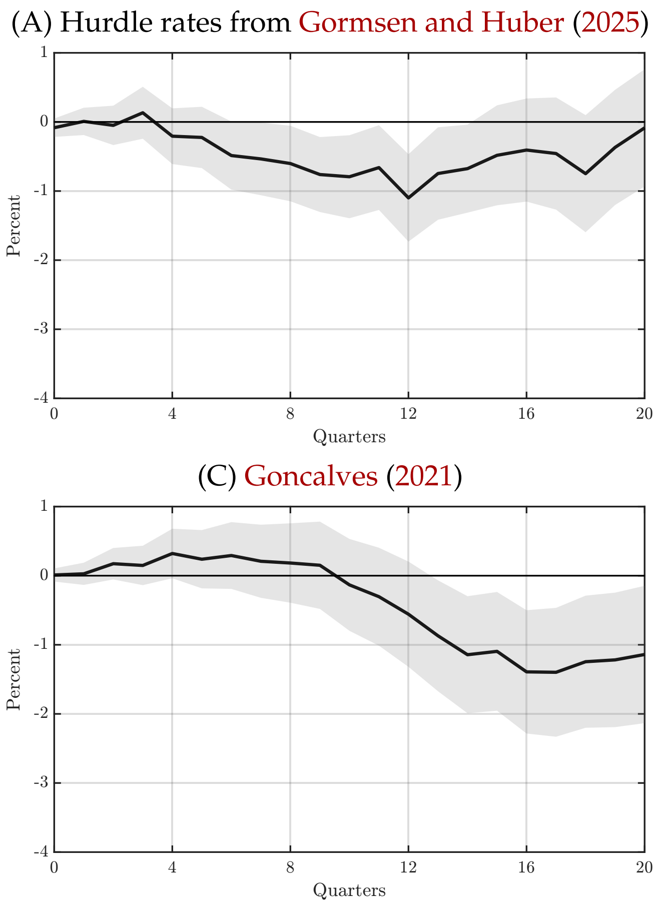
Baseline Estimations Using Cash Flow Duration In Section 3.4 we showed that our measure of long-term expected growth can be mapped into cash flow duration, which in the neoclassical framework pins down the semi-elasticity of investment. We check whether our results are consistent with those obtained by using cash flow duration directly, instead of simply the expected growth. Since cash flow duration cannot be observed, we run the main regression using four alternative measures. First, we combine our measure of long-term growth with manually-collected data on firms' *perceived* cost of capital from Gormsen and Huber (2025) to directly compute cash flow duration as $\mathcal{D} = (r - g)^{-1}$. Second, we follow Kroen et al. (2021) and directly compute cash flow duration using high-frequency variation in stock prices. We describe the details on how we construct this variable in Appendix B.3. Third, we take the equity duration measure from Goncalves (2021) off the shelf and run our baseline specifications. Fourth, we use the (inverse) book-to-market ratio as a proxy of duration.

Figure 9 presents the results of each cash flow duration measure. Panel (A) shows that our main results remain unchanged when computing duration using the Gordon growth formula and hurdle rates from Gormsen and Huber (2025). Panel (B) shows that when using the high-frequency approach, our

[26] Regarding financial constraints, our results seem consistent with those of Ottonello and Winberry (2020), where unconstrained firms have relatively stronger reactions to monetary policy shocks, through changes in the price of debt. In our case, that response is further amplified by long-term growth, which makes the present value of future cash-flows more sensitive to that price.

results hold qualitatively, though they are slightly smaller in magnitude.[27] Panel (C) reports results using equity duration and presents results consistent with our baseline measure of long-term growth. Panel (D) shows that "growth" firms are also more responsive to monetary policy shocks.

Figure 9: Heterogeneous Response Using Measures of Cash Flow Duration



Notes: Panels (A)-(D) present estimates of β^h in Equation (23), but using different measures of cash flow duration. Panel (A) is based on high-frequency stock price changes around FOMC announcements (for more details on the methodology, please refer to Appendix B.3). Panel (B) uses the Duration measure in Goncalves (2021). Panel (C) uses the inverse of the book-to-market ratio as proxy for duration. To reduce volatility at the firm level, we compute the average book-to-market ratio 4 quarters before the shock. Panel (D) uses duration measured as $(\widehat{r}_{it} - \widehat{\text{LTG}}_{it})^{-1}$, where $\widehat{r}_{it}$ is the predicted hurdle rate from Gormsen and Huber (2025), and $\widehat{\text{LTG}}_t$ is annualized assuming a four-year horizon. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

We see these results as favoring the neoclassical interpretation of firms' growth rates increasing the duration of cash flows, and therefore increasing valuation sensitivities to discount rates. According to the framework we presented in Section 2, investment semi-elasticities are proportional to cash flow duration in a standard neoclassical model, and duration is in turn determined by g. Since our baseline

[27] However, measuring cash flow duration using stock price reactions to monetary policy is subject to several important threats to the identification. First, monetary policy shocks are not "pure discounting" shocks and may contain information that affects expected cash flow growth. Second, firms with different durations have different cost of capital, so by using the same shock for all firms, we are assuming a "parallel shift" in the yield curve. In fact, figure C.4 shows that at the high-frequency level, the response of yields at the longer end of the curve is significantly smaller.

results can be obtained not by using g, but instead by using proxies of duration, our empirical evidence further validates the connection between both objects.

4.5 Discussion

We consider our results a relevant contribution to the literature on the transmission of monetary policy to investment. In particular, our main result suggests that high-growth firms, measured using analysts' expected long-term growth, are more sensitive to monetary policy. This result is both statistically and economically significant, where a one standard deviation higher expected long-term growth generates almost 2 percent higher decline in total investment in response to a 25 bps monetary policy shock. This is approximately 50 percent of the average effect of the same shock and significant throughout our 5-year horizon.

The fact that our results are highly significant and robust to different specifications is also surprising. Even after controlling for the main characteristics documented in the literature to affect investment, leverage, liquidity, size, and age, as well as their interactions with the monetary shock, we still find that expected long-term growth matters for the firms' response to monetary policy. These finding suggests that, on top of usual balance-sheet variables, expected long-term growth, and with that cash flow duration, is an additional source of heterogeneity that is relevant for understanding monetary policy transmission to investment.

When we turn to specific capital types, our findings may seem at odds with those in Döttling and Ratnovski (2023). Namely, they find that stock prices and investment of firms with relatively more intangible assets respond less to monetary policy, that those firms are also less responsive to monetary policy, and that, in particular, intangible investment responds less than physical capital. The first result suggests that firms with a higher share of intangible assets are associated with lower expected growth. In that sense, the fact that firms with a high intangible share are less sensitive to the shock is consistent with our results. Conceptually, rather than focusing on intangible intensity, we center our attention on differences in long-term growth expectations. Even though intangible-intensive firms are associated with high $\widehat{\text{LTG}}$ (pairwise correlation of 0.23), once we focus on high-growth firms, intangible capital has a similar, and even somewhat larger, elasticity than physical capital.[28]

Beyond the implications for investment dynamics, our results may also have implications for aggregate productivity beyond the business cycle frequency. In particular, if high-growth firms or projects

[28] Moreover, as we discussed in Section 4.4 (see footnote), the conditions under which stock price changes around monetary announcements can be interpreted as identifying cash flow duration are unlikely to hold in the data.

are also more innovative, then monetary expansions could generate an increase in innovation that could potentially have lasting effects. It would be interesting to see if our results hold when looking at innovations measures like citations, number of patents, among others.[29] Regarding the effects of monetary policy on productivity, evidence is somewhat mixed. On one side, papers like Moran and Queralto (2018) and Jordà et al. (2024) suggest that monetary policy positively impacts productivity, while on the other, Liu et al. (2022) argues that when interest rates are low enough, an increase in market concentration dominates the valuation effect, decreasing aggregate productivity.

We think our results encourage further research in this area. On one hand, we find that firms with high expected growth are more sensitive to monetary policy shocks, and on the other hand, this effect is larger for financially unconstrained firms. If high-growth firms are the ones driving innovation, then monetary expansions could have a hysteresis effect through the relative expansion of more innovative investments. Further, the amplification of the effect for high-liquidity firms could have other policy implications, as high-growth projects (like innovation) seem to rely more extensively on internal resources.

5 Conclusion

In this paper, we studied how firms' expected long-term growth affects the transmission of monetary policy to investment. Using a stylized framework, we show that cash flow duration, and thus long-term growth, is a key object for the interest rate elasticity of investment. In particular, if we assume that within an industry firms produce using the same technology, we are able to identify the partial equilibrium response of investment to a change in the interest rate, which is proportional to the firm's pre-shock duration and a time-invariant parameter that governs the marginal cost of investment.

We then used analyst forecasts to construct a proxy for long-term growth expectations, which we used in our main empirical analysis. Among our main findings, we find that investment in high-growth firms is significantly more sensitive to monetary policy, even after controlling for other firm observables and their interaction with the shock. In particular, in response to a 25 bps contractionary shock, a standard deviation higher long-term growth is associated with an almost 2 percent larger decline in investment. In addition, we find some evidence that point estimates are slightly larger for intangible capital, with a peak estimate of 2 percent, relative to the 1.5 percent estimate for physical capital. Both results seem robust to different samples and measurement assumptions. We also present evidence that leverage, and especially liquidity, amplify our baseline effect.

[29] In fact, when looking at aggregate data, we do see that in response to a monetary expansion, the number of patents increases as well as the market value of these new patents, which we measure using the innovation index by Kogan et al. (2017). These results are available upon request.

Finally, given that our results suggest that higher-growth firms are more sensitive to monetary policy, further work could use this mechanism to understand potential hysteresis effects. Namely, that monetary policy could potentially affect firms' incentives to invest in innovation and, with that, have lasting effects on output. While there is some research on this area (e.g. Moran and Queralto, 2018; Ma and Zimmermann, 2023; Jordà et al., 2024), we believe having a better understanding of how cash flow duration could generate real effects of monetary policy beyond business cycle frequency is a fruitful avenue for future research.

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A Extension of the Model to High and Low Growth Firms

In this version of the model, there are *newborn* firms and *mature firms* that have different technology and adjustment cost parameters. Time is continuous, and firms have a life cycle: they are born, then become mature with Poisson rate θ, and when they are mature, they die with Poisson rate λ. Throughout the rest of this section, we use N to refer to newborn firms and M to mature firms. The problem of the firms now depends on their stage. First, newborn firms solve the following problem:

$$V^N(K_t) = \max_{(I_s)_{s\geq t}} \int_t^{\infty} e^{-\int_s^t r_u \mathrm{d}u} \left(\Pi^N(K_s, w_s) - p_{K,s}\left(I_s - \Phi^N(I_s, K_s)\right) + \theta\left(V^M(K_t) - V^N(K_t)\right)\right) \mathrm{d}s, \quad \text{(A.1)}$$

$$\text{s.t. } \dot{K}_t = I_t - \delta K_t. \quad \text{(A.2)}$$

While mature firms solve the following:

$$V^M(K_t) = \max_{\{I_s\}_{s\geq t}} \int_t^{\infty} e^{-\int_s^t r_u \mathrm{d}u} \left(\Pi^M(K_s, w_s) - p_{K,s}\left(I_s - \Phi^M(I_s, K_s)\right) - \lambda V^M(K_t)\right) \mathrm{d}s, \quad \text{(A.3)}$$

$$\text{s.t. } \dot{K}_t = I_t - \delta K_t. \quad \text{(A.4)}$$

Because V^N does not enter into V^M, it is easier to solve first for V^M, and then use that solution to solve V^N. The first-order necessary conditions for *mature* firms are:

$$p_{K,t}\left(1 + \Phi_I^M(I_t, K_t)\right) = q_t^M, \quad \text{(A.5)}$$

$$\Pi_K^M(K_t; w_t) - p_{K,t}\Phi_K^M(I_t, K_t) - q_t^M(\delta + \lambda) = r_t q_t^M - \dot{q}_t^M, \quad \text{(A.6)}$$

$$\lim_{t\to\infty} e^{-\int_0^t r_u \mathrm{d}u} q_t^M K_t \leq 0, \quad \text{(A.7)}$$

Integrating Equation (A.6) forward, we get

$$q_t^M = \int_t^{\infty} e^{-\int_s^t (r_u + \delta + \lambda)\mathrm{d}u} \left(F_K^M(K_s) - p_{K,s}\Phi_K^M(I_s, K_s)\right) \mathrm{d}s. \quad \text{(A.8)}$$

If we make the same special assumptions as in the simple case:

$$\text{Newborn firms: } \Pi^N(K, w) = A^N(w)K, \; \Phi^N(I, K) = \phi^N(i)K$$

$$\text{Mature firms: } \Pi^M(K, w) = A^M(w)K, \; \Phi^M(I, K) = \phi^M(i)K,$$

then we can also get a baseline path for mature firms, where i^M remains constant. Putting that into Equation (A.8) we have

$$q^M = \frac{A^M(w) + p_K\left(\phi^M(i^M) - \phi^{M\prime}(i^M)i^M\right)}{r+\delta+\lambda}$$

Now, since V^M is homogeneous of degree 1 in K, we can solve $V^M(K_t) = q^M K_t$ with the following equation:

$$\begin{aligned} V^M(K_t) =& q^M K_t = \left(\left(A^M(w) - p_K(i^M + \phi^M(i^M)) - \lambda q^M\right)\int_t^\infty e^{-(r-i^M+\delta)s}\mathrm{d}s\right)K_t \\ \implies q^M =& \frac{A^M(w) - p_K(i^M+\phi^M(i^M))}{r - \underbrace{i^M + \delta}_{\equiv g_M} + \lambda} \end{aligned}$$

With this result, we can now proceed to solve the newborn firms case. For those firms, the first-order necessary conditions are:

$$p_{K,t}\left(1+\Phi_I^N(I_t,K_t)\right) = q_t^N, \tag{A.9}$$

$$\Pi_K^N(K_t;w_t) - p_{K,t}\Phi_K^N(I_t,K_t) - q_t^N(\delta+\theta) + \theta q_t^M = r_t q_t^N - \dot{q}_t^N, \tag{A.10}$$

$$\lim_{t\to\infty} e^{-\int_0^t r_u \mathrm{d}u} q_t^N K_t \leq 0, \tag{A.11}$$

Since on a baseline path, we already have a solution for q^M, we can solve for q^N by treating q^M as given, and integrating forward:

$$q^N = \frac{A^N(w) + p_K\left(\phi^N(i^N) - \phi^{N\prime}(i^N)i^N\right) + \theta\frac{A^M(w) - p_K(i^M+\phi^M(i^M))}{r-g_M+\lambda}}{r+\delta+\theta}$$

We can, again, use the homogeneity of the functions to solve $V^N(K_t)$ with the linear form $q^N K_t$:

$$\begin{aligned} V^N(K_t) =& q^N K_t = \left(\left(A^N(w) - p_K(i^N+\phi^N(i^N)) - \theta q^N + \theta\frac{A^M(w) + p_K\left(\phi^{M\prime}(i^M) - \phi^M(i^M)\right)}{r-g_M+\lambda}\right)\int_t^\infty e^{-(r-g_M)s}\mathrm{d}s\right)K_t \\ \implies q^N =& \frac{1}{r-g_N+\theta}\left(A^N(w) - p_K(i^N+\phi^N(i^N)) + \theta\frac{A^M(w) + p_K\left(\phi^{M\prime}(i^M) - \phi^M(i^M)\right)}{r-g_M+\lambda}\right) \end{aligned}$$

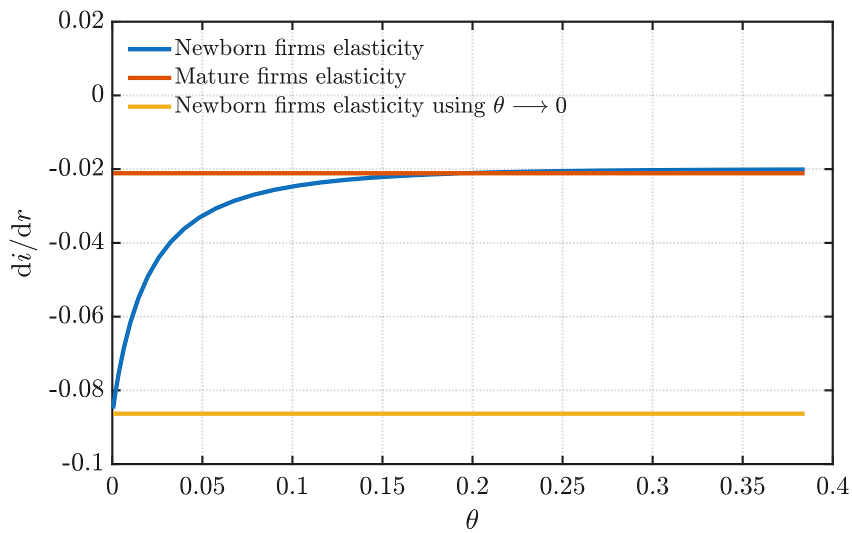
With the exponential adjustment cost function we previously assumed, we can log-differentiate each q. We use the notation $\Lambda_j = A_j(w) - p_K\left(i^j + \phi^j(i^j)\right)$, for $j \in \{N, M\}$ and use $\mathrm{d}i_j/\mathrm{d}r = (1/\varphi^j) \times (\mathrm{d}\log q_j/\mathrm{d}r)$ to get (after ignoring all the general equilibrium effects through prices):

$$\frac{\mathrm{d}i^N}{\mathrm{d}r} = -\frac{1}{\varphi_N}\left[\frac{1}{r-g_N+\theta} + \left(\frac{1}{r-g_M+\lambda}\right)\frac{1}{1+\dfrac{\Lambda_N}{\theta\Lambda_M}(r-g_M+\lambda)}\right] \tag{A.12}$$

$$\frac{\mathrm{d}i^M}{\mathrm{d}r} = -\frac{1}{\varphi_M}\left(\frac{1}{r - g_M + \lambda}\right) \tag{A.13}$$

Note that, when firms are expected to mature faster (larger θ), the mature growth rate is more relevant. In the limit, where $\theta \longrightarrow \infty$, $\mathrm{d}i^N/\mathrm{d}r = -(1/\varphi_N) \times (r - g_M + \lambda)^{-1}$. In the opposite extreme, the limiting case of $\theta \longrightarrow 0$ yields $\mathrm{d}i^N/\mathrm{d}r = -(1/\varphi_N) \times (r - g_N)^{-1}$. The empirical implication of this fact is that, even if a firm's short-run growth is different from its long-term growth, it is the latter that determines investment elasticity, provided that the long-run is *near enough*. To see an example, Figure A.1 shows the investment elasticity of newborn and mature firms. To keep the comparison simple, we assume $\varphi^N = \varphi^M = 5$, $\lambda = 0$, and $A^N(w) = 0.5\ A^M(w) = 0.3$. With an interest rate of $r = 0.1$ and a depreciation rate $\delta = 0.08$. The resulting growth rates when $\theta \to 0$ are $g_N = 7.7$ percent and $g_M = 0.53$ percent. Despite the growth rates being very different, we see that the growth sensitivity quickly becomes more negative as θ increases (while keeping the rest of the equation fixed), with the difference becoming negligible after $\theta = 0.05$.

Figure A.1: Investment elasticity by firm type, and different θs



B Data Appendix

B.1 Main variables and definitions

1. **Investment.** Real investment time series are constructed using the change in PPE (`ppentq`) and deflated by an investment price deflator.
2. **Physical Capital Stock.** We construct real capital stock for firm j in sector s at time t, $k_{j,s,t}$ by using the perpetual-inventory method (PIM).[30] Namely, we take the first observation of the level of gross property, plant and equipment (`ppegtq`). From the next period onwards, nominal capital stock is constructed using the previous value plus net investment. Capital is then deflated using the same price deflator as for investment.

   If a firm has a missing observation of `ppentq`, located between two periods with non-missing observations we estimate its value using a linear interpolation with the values of `ppentq` right before and after the missing observation; if two or more consecutive observations are missing we do not do any imputation.[31] We only consider investment spells with a given number of quarters (see Appendix B.2).
3. **Intangible Capital Stock.** We define an initial capital stock of 0 for the firm's first year in Compustat. Then, we construct the series by considering quarterly R&D expenditures (`xrdq`) and 30 percent of Selling, general, and administrative expenses (SG&A) as investments in intangible capital. To construct SG&A, we use `xsgaq` minus `xrdq` minus `xrdipq`. As in Peters and Taylor (2017), we leave `xsgaq` unchanged whenever `xrdq` exceeds `xsgaq` but is less than `cogsq` or as zero when `xsgaq` is missing.
4. **Depreciation rates.** We use industry-level depreciation rates from the Fixed Asset tables from (BEA) for physical capital. For intangible capital, we follow Benigno and Fornaro (2018) and set the depreciation rate equal to 15 percent, constant across firms and over time.
5. **Investment price deflator.** We use Nonfarm Business Sector Value-Added Output Price Deflator for All Workers as our investment price deflation (`IPDNBS`).
6. **Leverage.** The ratio of total debt (sum of `dlcq` and `dlttq`) and total assets (`atq`).
7. **Real sales growth.** Measured as log-differences in sales (`saleq`).
8. **Liquidity.** Cash and Short-Term Investments (`cheq`) over total assets `atq`.
9. **Tobin** q. Market-to-book value of the firm. Market value is defined as market equity plus the book value of debt.
10. **Age.** We define age as the max between the number of years the firm appears in the sample and the age from the foundation year on Jay Ritter's database.
11. **Book Equity.** Total assets (`atq`) minus total liabilities (`ltq`).
12. **Market Equity** Using monthly data from CRSP, we compute market equity as the product of the price (`prc`)

[30] As in most of the literature one firm-level investment, we take this approach as it is arguably easier to observe flows than stocks.

[31] Our results are essentially identical if we do not perform this interpolation. This is also fairly standard in the literature (see, e.g. Ottonello and Winberry, 2020; Meier and Reinelt, 2024).

times the number of shares outstanding (shrout).[32] We use the average market value when collapsing to the quarterly level.

13. **Book-to-market** Ratio of book equity to market equity. We report as missing observations with book-to-market (BM) ratio larger than 50 or less than 1/50.
14. **Payout Ratio** Net income (niq) minus change in book equity.
15. **OI/ME** We define operating income over market equity as oiadpq over the firm's market equity.

B.2 Sample selection

Following standard definitions from the literature, we exclude observations (in the same order as presented below) based on the following criteria:

1. Not incorporated in the United States (based on fic).
2. Native currency not U.S. Dollar (based on ISO currency code, curcdq).
3. Specific sectors:
   (a) Utilities (NAICS 22).
   (b) Financial Insurance and Real Estate (FIRE, NAICS 52 and 53).
   (c) Public Administration (NAICS 99).
4. Firm-quarter observations that satisfy one of the following conditions:
   (a) Non-positive R&D, SG&A, capital or assets.
   (b) Acquisitions (based on aqcy) exceed 5 percent of total assets (in absolute terms).
   (c) Investment rate is in the top/bottom 0.5 percent of the distribution.
   (d) Investment spell is shorter than 40 quarters, unless they are still in the sample in the final period.
   (e) R&D-over-total assets greater than 100%.
   (f) Net current assets as a share of total assets higher than 10 or below -10.
   (g) Leverage higher than 10 or negative.
   (h) Quarterly real sales growth above 1 or below -1.
   (i) Negative sales or liquidity.

Table B.1 reports details of our data cleaning. We also winsorize all independent variables at the top/bottom 0.5 percent of their cross-sectional distribution to reduce the influence of outliers. We also winsorize cumulative differences for the dependent variables at the top/bottom 0.5 percent. After all this cleaning procedure, we select as baseline period 1994q1-2019q4.

[32] For observations where CRSP does not report the actual closing, we use price alternate altprc for the price. This variable contains the last non-missing price in the month.

Table B.1: Data Cleaning, direct computation of net investment

	Observations	Share (%)
Full sample	1,435,510	100
Drop specific industries	506,177	35.26
Drop negative R&D or SG&A and weakly negative capital or assets	13,271	0.92
Drop firm-quarter observations with acquisitions larger than 5 percent of assets	22,882	1.59
Drop observations where the investment rate is in the top and bottom 0.5 percent of the distribution	6,254	0.44
Drop if investment spell is shorter than 40 quarters	296,314	20.64
Drop firm-quarter observations where R&D, liquidity, leverage, and sales are outliers	33,587	2.34
Final Sample	557,025	38.80

Notes: Shares on the last column are relative to the original sample. For detail on the sample selection see text.

B.3 Constructing Duration Using Asset Prices

We follow Kroen et al. (2021) and measure cash flow duration using high-frequency changes in asset prices around FOMC announcements. In particular, we look at the response of individual stock prices to identified monetary policy shocks to directly estimate duration as the semi-elasticity of the firms' market value to an interest rate shock. We have that

$$\mathcal{D} \equiv \frac{\mathbb{E}_0\left[\int_0^\infty t\exp(-rt)CF_t dt\right]}{\mathbb{E}_0\left[\int_0^\infty \exp(-rt)CF_t dt\right]} = -\frac{\mathrm{d}\log V_0}{\mathrm{d}r}. \tag{B.1}$$

Let $r_i = d\log V_0$ be the response of the firms' market value around an FOMC announcement and $\varepsilon_t^{\text{mp}} = dr$, then we can estimate duration $\mathcal{D}$ by running the following linear regression:

$$r_i = \alpha_i + \mathcal{D}_i \varepsilon_t^{\text{mp}} + e_t. \tag{B.2}$$

We estimate Equation (B.2) using Bauer and Swanson (2023) monetary policy shocks as $\varepsilon_t^{\text{mp}}$ and intra-day asset price data from the NYSE Trade and Quote (TAQ) database. Namely, we compute the 30-minute return for each available stock price over the same 30-minute window used for the monetary policy shocks. Also, because cash flow duration typically changes over time (e.g., as firms age or grow), we estimate Equation (B.2) using a rolling window of 50 periods, for which we require firms to have data on at least 30 periods.

C Additional Figures

Figure C.1: Time Series of Monetary Shocks

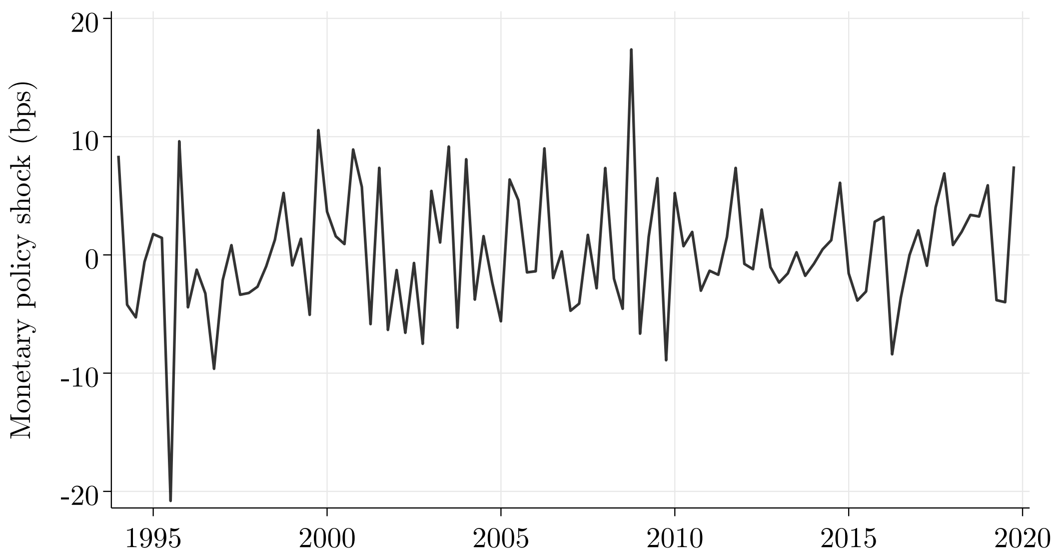
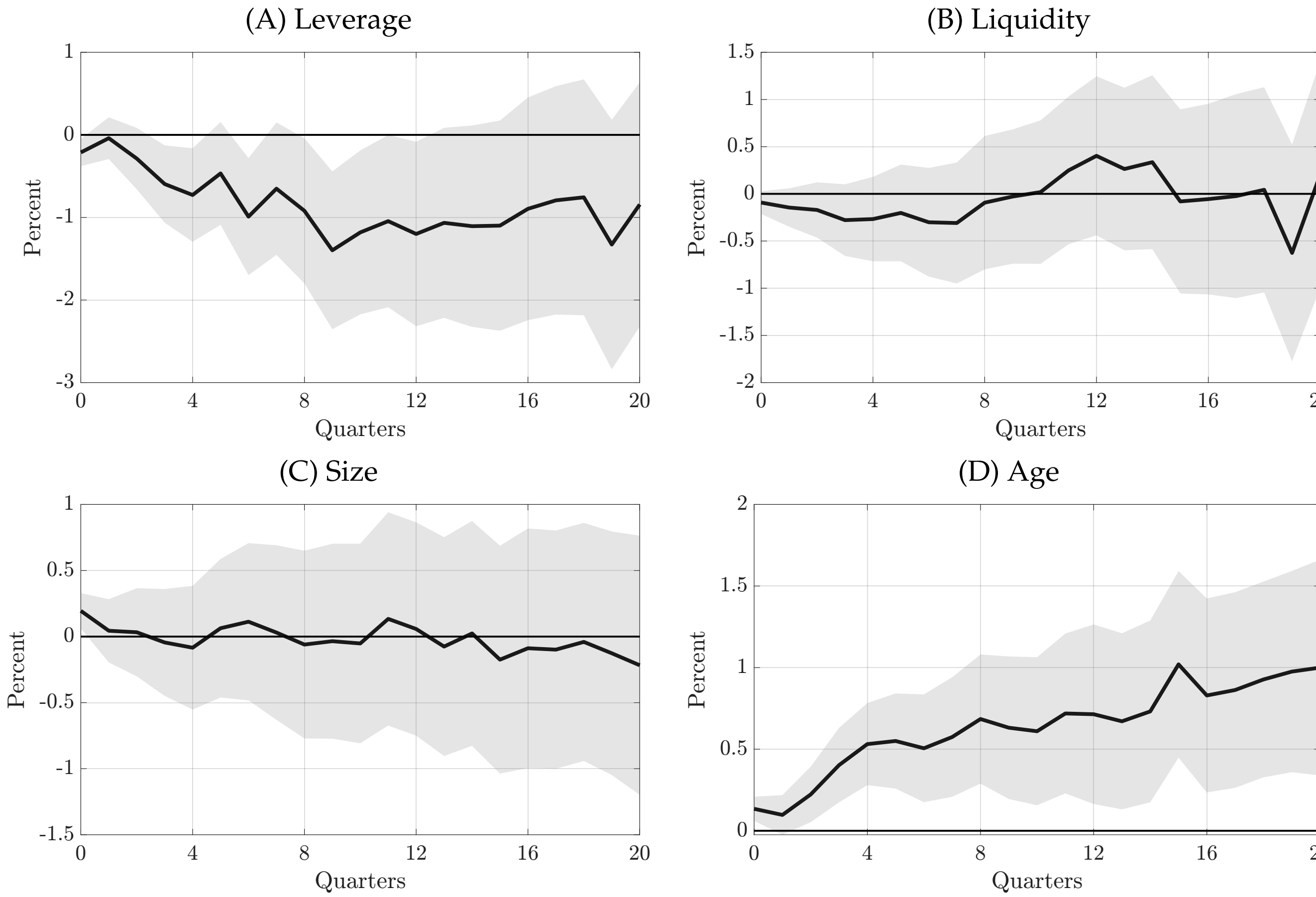
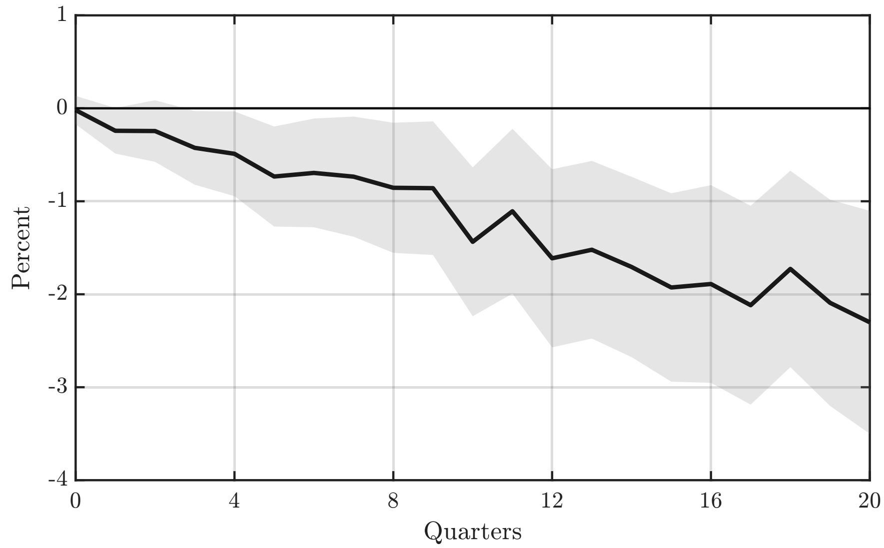


Figure C.2: Heterogeneous Response of Total Capital Conditional on Other Firm Observables



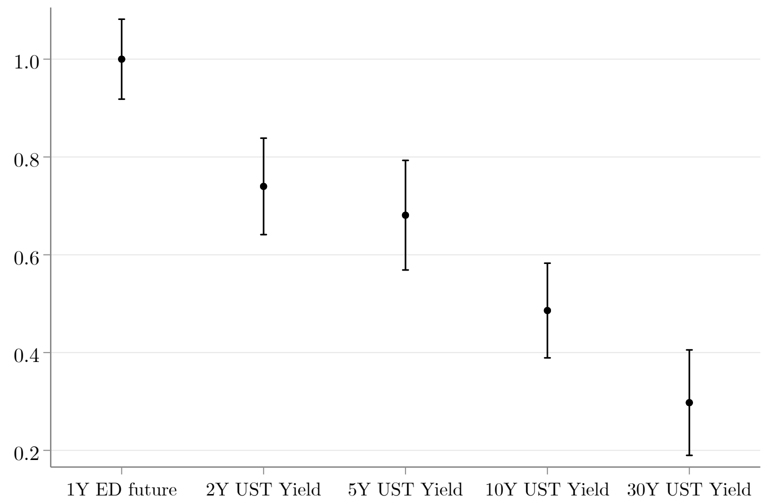
Notes: This figure presents estimates of all other firm-level coefficients included in Equation (23). Leverage, liquidity, size and age are standarized. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.3: Robustness on Differential Effect—Raw Long-Term Growth Forecasts



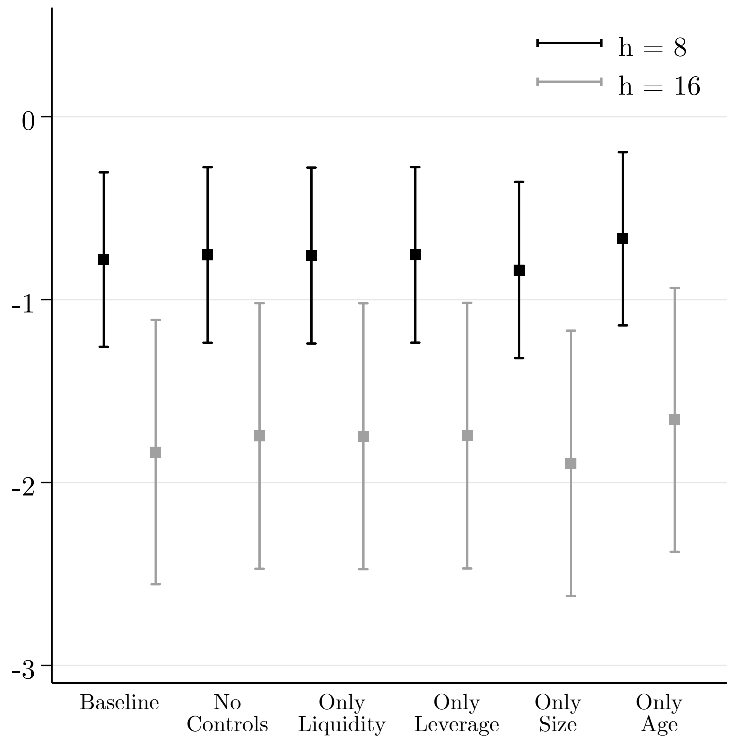
Notes: This figure presents estimates of β^h in Equation (23), but using actual long-term growth forecasts LTG, instead of $\widehat{\text{LTG}}$. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.4: High-Frequency Effect of Monetary Policy Shocks Along the Yield Curve



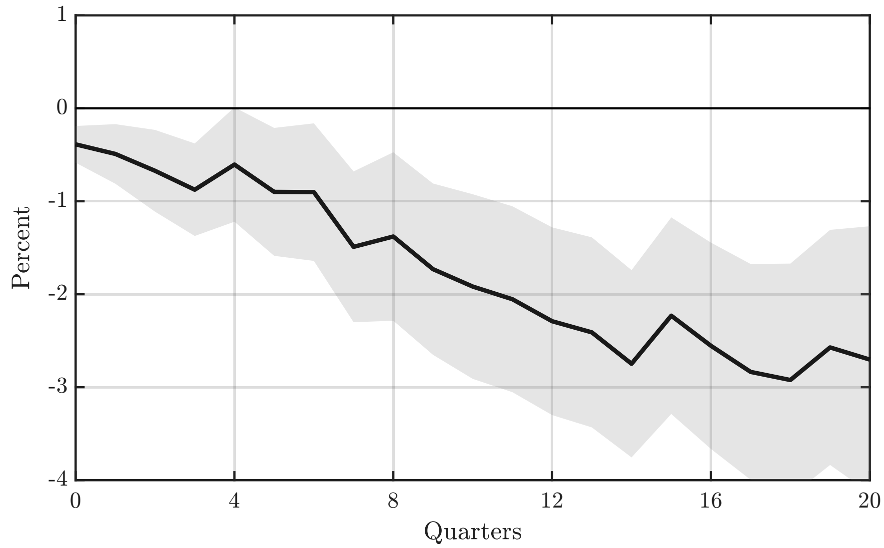
Notes: This figure presents estimates of β after running the regression $y_t = \alpha + \beta \text{mps}_t^{\perp} + u_t$, where y_t denotes yields of different maturities and $\text{mps}_t^{\perp}$ represent Bauer and Swanson (2023) orthogonalized monetary policy shocks. The shock is rescaled so that a unit shock increases the 1-year Eurodollar future by one. Brackets represent 95% confidence intervals.

Figure C.5: Robustness Under Different Set of Controls Interacted with Shock



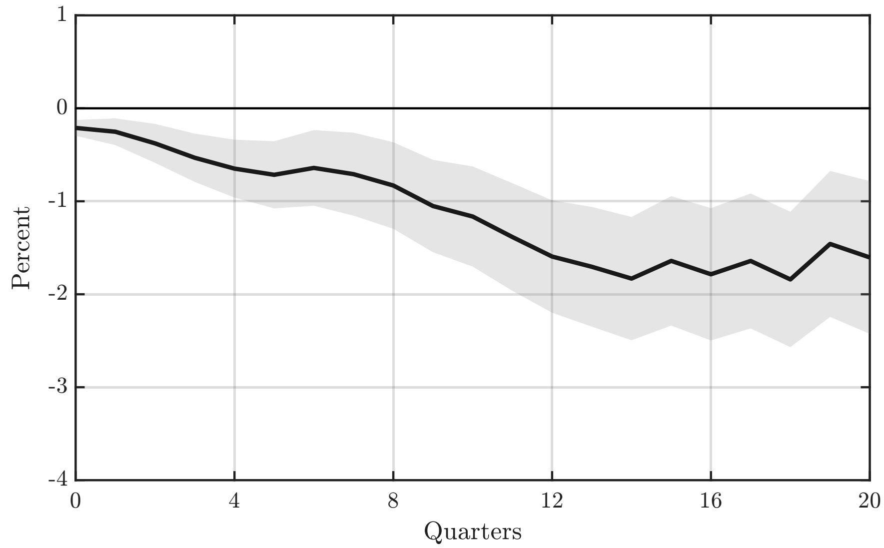
Notes: This figure presents estimates of β^h in Equation (23), but using different sets of controls interacted with the monetary policy shock. The rest of the covariates remain unchanged relative to Equation (23). For illustrative purposes, we only report results for $h = 8$ and $h = 16$. The first column shows our baseline results. The second column does not include any other variable (besides $\widehat{\text{LTG}}$) interacted with the shock. The remaining columns only include one interaction with the shock besides $\widehat{\text{LTG}}$.

Figure C.6: Robustness on Differential Effect—No SG&A



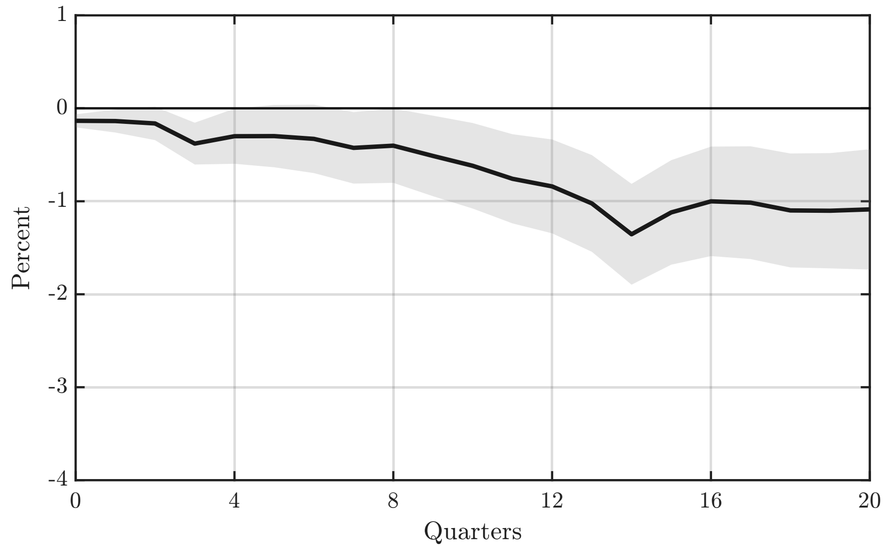
Notes: This figure presents estimates of β^h in Equation (23), excluding SG&A expenses in the construction of intangible capital. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.7: Robustness on Differential Effect—Average Forecast as Consensus



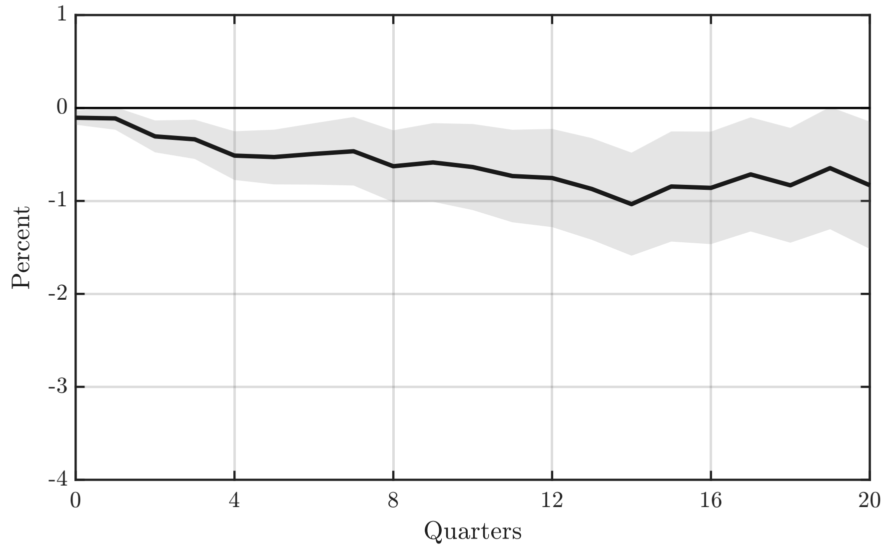
Notes: This figure presents estimates of β^h in Equation (23), but using the average forecast as the consensus to estimate $\widehat{\text{LTG}}$. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.8: Robustness on Differential Effect—Using Sum of High-Frequency Monetary Policy Shocks



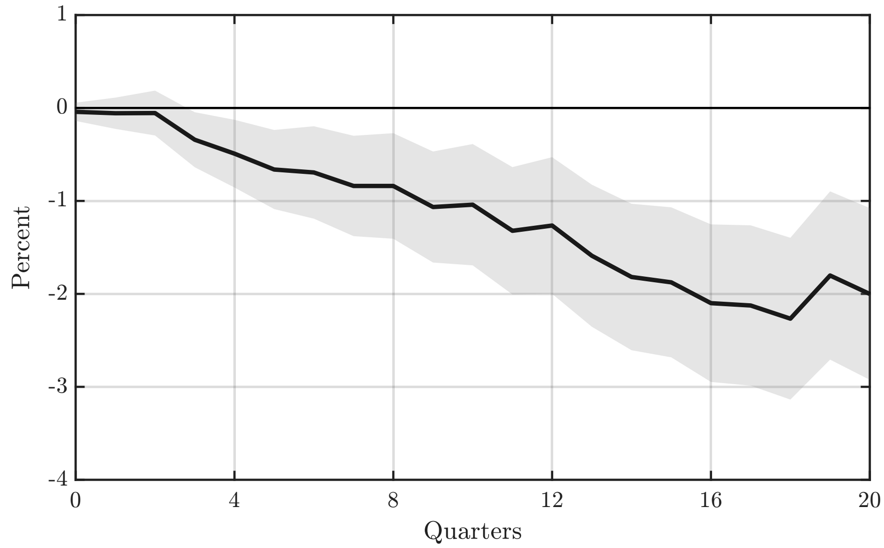
Notes: This figure presents estimates of β^h in Equation (23), but aggregating monetary policy shocks $\varepsilon_t^{\text{mp}}$ using the (unweighted) sum of shocks when aggregating them to quarterly. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.9: Robustness on Differential Effect—Using Ottonello and Winberry (2020) Firm-Level Demeaned Specification



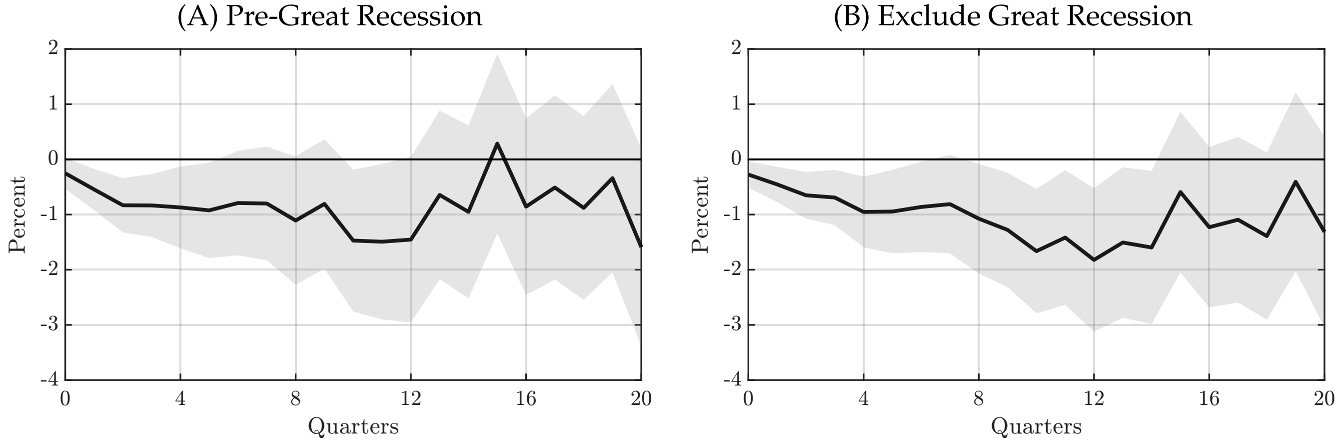
Notes: This figure presents estimates of β^h in Equation (23), but using firm-level demeaned $\widehat{LTG}_{it}$, that is $\widehat{LTG}_{it} - \mathbb{E}_i[\widehat{LTG}_{it}]$ following the specification in Ottonello and Winberry (2020). Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.10: Robustness on Differential Effect—Using Monetary Policy Shocks from Jarociński and Karadi (2020)



Notes: This figure presents estimates of β^h in Equation (23), but using monetary policy shocks from Jarociński and Karadi (2020), which accounts for central bank information shocks. Aggregation of the shocks to quarterly is done in the same way as for our baseline regression. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

Figure C.11: Robustness on Differential Effect—Different Sample Periods.



Notes: This figure presents estimates of β^h in Equation (23) for total capital. Panel (A) reports results for the period prior to the Great Recession (1994q1-2007q4). Panel (B) excludes the Great Recession. For this, we follow Nakamura and Steinsson (2018); Meier and Reinelt (2024) and discard 2008Q3 to 2009Q2 and do not regress post-2009Q2 outcomes on pre-2008Q3 shocks. Shaded areas represent 90% confidence intervals, with standard errors clustered by firm and industry-time (3-digit NAICS).

D Additional Tables

Table D.1: Expected Long Term Growth and Firm-Level Characteristics

	(1) Weigthed by Number of Analysts	(2) Weighted by ME	(3) Unweighted
BM	-0.055***	-0.077***	-0.060***
	(0.004)	(0.020)	(0.004)
OI/ME	-0.101***	-0.113***	-0.101***
	(0.005)	(0.017)	(0.004)
Asset growth	0.039***	0.055***	0.041***
	(0.003)	(0.008)	(0.002)
Payout ratio	-0.043***	-0.062***	-0.035***
	(0.003)	(0.017)	(0.002)
Beta	0.056***	0.111***	0.042***
	(0.005)	(0.015)	(0.004)
Time FE	Yes	Yes	Yes
Observations	141,115	141,115	141,115
R^2	0.206	0.224	0.136

Notes: This table presents results of estimating Equation (19) under different weights. All variables are expressed as cross-sectional percentiles. BM denotes book-to-market and OI/ME denotes operating income over market equity. Market equity is constructed using total shares outstanding and stock prices from CRSP. Firms' betas are calculated using a rolling regression over 5 years. Standard errors are reported in parentheses and clustered by firm and date. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Expected Long Term Growth and Firm-Level Characteristics—Average Forecast

	(1) Weigthed by Number of Analysts	(2) Weighted by ME	(3) Unweighted
BM	-0.054***	-0.077***	-0.060***
	(0.004)	(0.020)	(0.004)
OI/ME	-0.102***	-0.114***	-0.101***
	(0.005)	(0.018)	(0.005)
Asset growth	0.040***	0.055***	0.042***
	(0.003)	(0.009)	(0.002)
Payout ratio	-0.044***	-0.063***	-0.035***
	(0.003)	(0.017)	(0.002)
Beta	0.058***	0.113***	0.044***
	(0.005)	(0.015)	(0.004)
Time FE	Yes	Yes	Yes
Observations	141,115	141,115	141,115
R^2	0.205	0.222	0.136

Notes: This table presents results of estimating Equation (19) under different weights. All variables are expressed as cross-sectional percentiles. BM denotes book-to-market and OI/ME denotes operating income over market equity. Market equity is constructed using total shares outstanding and stock prices from CRSP. Firm's betas are calculated using a rolling regression over 5 years. Standard errors are reported in parentheses and clustered by firm and date. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$