Monetary Policy, Extrapolation Bias and Misallocation

Yuchen Chen*

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Abstract

This paper studies the distributional effects of earning extrapolation bias on monetary transmission. Empirically, over-pessimistic firms with lower earning forecasts have higher investment elasticity to monetary shocks, which is more pronounced in the advertising-intensive industries. I develop a dynamic model to quantify the effects of extrapolation bias in a frictional product market, where firms extrapolate over idiosyncratic productivity news when making decisions on physical investment and customer acquisition. The model implies that firm-level overreaction *amplifies* the allocative efficiency of monetary easing: it raises aggregate productivity as capital flows to high markup firms. Moreover, the rise in aggregate output is underestimated by 57% if we assume rational expectation.

JEL codes:

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Department of Finance, Gies College of Business, University of Illinois Urbana-Champaign, Champaign, IL 61821. E-mail: chen3912@illinois.edu.

1 Introduction

A large psychology literature documents that decision-makers' forecasts of future circumstances appear overly influenced by previous news. This critical feature of belief formation is captured by extrapolative expectations that Bordalo et al. (2018) formulated: firm owners extrapolate over productivity news in the last period when making future earning forecasts. Other studies also empirically show a degree of overreaction in this type of extrapolative expectation at the firm level. How does this belief formation process affect the transmission of monetary policy? However, the aggregate effect of firm-level overreaction remains unclear.

This paper aims to understand the role of extrapolation bias in monetary transmission. Baqaee, Farhi, and Sangani (2021) propose a supply-side channel for the transmission of monetary policy through which the "supply shock" generates procyclical aggregate productivity assuming that the firm owner (manager) has a rational expectation, which is not valid in the data. Whether the extrapolative expectation dampens or amplifies the impact of monetary policy remains unknown, but this is critical in evaluating the allocative efficiency of monetary policy.

The baseline empirical analysis estimates how heterogeneous corporate investment sensitivities regarding a monetary shock depend on their measured extrapolation bias on future earnings. I measure monetary shocks as the changes in Fed Funds rates in narrow windows around FOMC announcements. The firm extrapolates when forecasting future earnings. The forecast error is defined as the difference between realized earnings and the manager's forecast value, which is predictable and displays some degree of overreaction. Therefore, I use it as a proxy for extrapolation bias. In addition, I use analyst's long-term earning growth forecast error as another proxy for a robustness check.

Empirically, I find that overpessimistic firms, i.e., firms with lower earning forecasts relative to the realized values, are more responsive to monetary shocks in their investments in both physical and customer capital. Specifically, having one standard deviation higher in the manager's forecast error implies that the firm is 1.19 times more responsive in physical capital investment and 0.7 times more responsive in customer capital investment compared to firms on average. These differences across firms in accumulated capital are significant and persistent for up to three years. In addition, the fact that extrapolation bias drives these heterogeneous sensitivities is particularly strong in the advertising-intensive industry.

To interpret these empirical results, I embed a dynamic directed search model of heterogeneous firms into a benchmark New Keynesian framework. The full model consists of an investment sector, a household sector, and a New Keynesian block. Households earn wage income and profit from producers, supply labor as marketing workers or buyers, as well as saving through a risk-free bond. In the investment sector, heterogeneous firms extrapolate over firm-level productivity news they received in the previous period and invest in physical rental capital and customer capital, which are assumed to be complementary. They finance their investment using both internal funds and costly equity issuance. Every period, a continuum of firms compete and acquire new customers by offering an initial discount in a frictional search market to expand their scales using optimal pricing schedules. Firm owners tradeoff between the profitability of existing customers and the benefit of an additional customer: offering additional discounts lower the current profit but help expand firm's scale for long-term profit. Search frictions render the customer base a state variable for firm decision-making. An interest rate hike raises the rental rate of physical capital and reduces the benefit of acquiring new customers because of the complementarity. As a result, firms reduce investment.

Quantitatively, I first solve the model for steady-state equilibrium. I calibrate the model to match the ratio of intangible expenditure to total asset, equity issuance to total asset, the correlation between profitability and forecast errors, standard deviation and auto-correlation of profitability, and the ratio of buyer's time to seller's time. The dynamic effects of monetary policy are evaluated by a perfect foresight transition dynamics of positive innovation to the Taylor rule. The shock raises the nominal interest rate and lowers the inflation rate due to sticky prices, which raises the real rate. A higher real rate dampens investment demand through cash flow and discount rate channels. On the one hand, the higher rental cost of capital reduces firm's cash flow. On the other hand, the higher discount rate depresses output demand and, therefore, the price of output drops. Lower marginal cost turns into lower marginal revenue, and this heterogeneous pass-through reduces cash flow to a different extent. In the simulated panel, overpessimistic firms (compared to firms under rational expectation) that received negative productivity news show higher pass-through due to more constrained balance sheets. The effects of monetary policy on the expected marginal return of capital and cash flows are more pronounced for overpessimistic firms, which leads to a higher investment sensitivity to shocks, as in the data.

Finally, I quantify the effect of extrapolation bias on the allocative efficiency of monetary policy. Overpessimistic firms that are initially less productive overinvested (compared to firms under rational expectation). Due to the mean-reverting property of the productivity process, overpessimistic firms become productive and, thus, high markup firms later. Capital flows to high markup firms following expansionary monetary policy, achieving a higher allocation efficiency and aggregate output. The model can produce a positive correlation between expansionary monetary policy and aggregate productivity, as in the data, and this is hard to achieve in a model with rational expectations. A 25-basis-point interest rate cut raises the aggregate output by 0.035% with extrapolative expectation, while this number goes down to 0.015% with rational expectation. This result suggests the importance of extrapolation bias in evaluating the effectiveness of monetary easing. The sensitivity analysis suggests that the parameters which govern the customer acquisition process are quantitatively essential to understand the transmission of monetary policy.

Literature Review This paper contributes to five strands of literature.

The first literature studies the transmission of monetary policy to the aggregate economy through different channels: investment channel (firm balance sheet) (Jeenas (2019); Ottonello and Winberry (2020); Crouzet(2021); Morlacco and Zeke (2021)), consumption channel (McKay, Nakamura, and Steinsson (2016); Kaplan, Moll, and Violante (2018); Auclert (2019); Wong (2019)), bank lending channel (Bernanke and Blinder (1988, 1992), Kashyap and Stein (1995, 2000), Bernanke and Gertler (1995), Drechsler, Savov and Schnabl (2017), and Ippolito, Ozdagli and Perez-Orive (2018)), mortgage refinancing channel (Wong (2016); Berger et al. (2018); Eichenbaum et al. (2018); Beraja et al. (2019)), inflation expectations channel and exchange rate channel. Previous studies emphasize the role of financial frictions in the transmission of monetary policy. I contribute to this literature by studying the investment channel in a frictional product market where agents have belief frictions in their perceived future investment opportunities.

Second, I contribute to the literature that studies the heterogeneous effects of monetary policy on corporate decisions. Previous studies argue that the firm-level response depends on size (Gertler and Gilchrist (1994), Morlacco and Zeke (2021)), default risk (Ottonello and Winberry (2020)), debt structure (Ippolito, Ozdagli and Perez-Orive (2018), Crouzet (2021), Chen (2021), Darmouni, Giesecke, and Rodnyansky (2021)), labor force attachment (Bergman, Matsa, and Weber (2020)), liquidity (Kashyap et al. (1994); Jeenas (2019)), or age (Cloyne et al. (2018)). In Appendix D, I show that my results are robust to controlling for these other firm characteristics.

Third, this paper also builds on another macro-finance literature that studies the departure from rational expectations. This paper is closely related to some recent work that combines extrapolative expectation with the financial friction amplification mechanisms in a macro-finance framework include Bordalo et al. (2018), Maxted (2020), Krishnamurthy and Li (2020), Farhi and Werning (2020), Caballero and Simsek (2020) and Bordalo et. al. (2021). I add to this literature by studying the aggregate effect of the interaction between belief friction and product market friction. Another strand of work studying departures from rationality in the form of partial information and inattention include Coibion and Gorodnichenko (2015), Kozlowski et al. (2017), Adam et al. (2017), Bhandari et al. (2019), Falato and Xiao (2020), Schaal and Taschereau-Dumouchel (2020), Bianchi et al. (2020).

Fourth, this paper contributes to the marketing and industrial organization literature on the role of customer capital for firm in a frictional product market. This idea was first introduced by Phelps and Winter (1970), and formalized by Gottfries (1986), Klemperer (1987), Farrell and Shapiro (1988), and Bils (1989), among others. The focus on extrapolation bias, pricing and interest rate further differentiate my work from previous studies of the customer capital implication for industry concentration (Morlacco and Zeke, 2021), firm investment dynamics (Gourio and Rudanko, 2014b), firms' life cycle (Perla, 2019; Roldan-Blanco and Gilbukh, 2020), firm size distribution (Luttmer et al., 2006), R&D and economic growth (Cavenaile and Roldan-Blanco, 2020), export market penetration (Arkolakis, 2010), trade (Drozd and Nosal, 2012), financing and stock returns (Dou, Ji, Reibstein, and Wu, 2021) and international prices (Fitzgerald and Haller, 2014).

Finally, this paper also speaks to a broad literature that studies the macro effect of micro-level heterogeneity, in terms of the methodology, for example Ma, Ropele, Sraer and Thesmar (2020). In particular, it is related to a growing literature that studies the redistribution effects of monetary policy. For example, Algan and Ragot (2010), Gornemann et al. (2012), Eggertsson and Krugman (2012), Jermann et al. (2014), Auclert (2016) and Baqaee, Farhi and Sangani (2020). In particular, Baqaee, Farhi and Sangani (2020) shows that the first-order effects of monetary policy on aggregate productivity comes from the redistribution effects of monetary policy. I introduce extrapolative expectation into a Heterogeneous Agents New Keynesian framework.

The rest of this paper is organized as follows. Section 2 provides empirical evidence that firm-level responses to monetary policy varies with firm's earning forecast errors. Section 3 develops a New Keynesian Heterogeneous Agents (HANK) model that replicates and explains the empirical results. Section 4 and 5 calibrates the model, details the model solutions and discusses the model implications on cross-sectional allocation efficiency and aggregate quantities. Section 6 performs the sensitivity analysis with respect to model parameters. Section 7 concludes.

2 Empirical Results

This section introduces the data and discusses the construction of key variables for the empirical exercise. I first document the main empirical results: 1) Overpessimistic firms disproportionately cut their investments on both physical and customer capital following an unexpected interest rates hike, compared to firms on average in the same industry. Therefore, their sales growth drops further. 2) The differential investment responses by extrapolation bias is particularly pronounced in advertising intensive industries.

2.1 Data

The main empirical exercise combines identified exogenous monetary policy shocks measured using high frequency fed funds rate with aggregate time series data from Federal Reserve Bank, quarterly firm-level accounting variables for publicly listed U.S. companies from Compustat and firm-level earning forecast values from I/B/E/S.

2.1.1 Monetary Policy Shocks

I use the measures of monetary policy shocks from Gurkaynak, Sack and Swanson (2005) and Gorodnichenko and Weber (2016) in the baseline analysis. They measure monetary shocks using the high-frequency, even-study approach, pioneered by Rudebusch (1998) and Kuttner (2001) and Cochrane and Piazzesi (2002).[1] Specifically, the monetary policy shock is measured as the changes in the current month's federal funds futures rate in a 30 minutes' narrow window around FOMC announcement.[2] I define shock ϵ_t^m as

$$\epsilon_t^m = \tau(t) \times (ffr_{t+\Delta_+} - ffr_{t-\Delta_-}), \tag{1}$$

where t is the time of the monetary announcement. ffr_t is the implied Fed Funds Rate from a current-month Federal Funds future contract at time t, Δ_+ and Δ_- control the size of the time window around the announcement, and $\tau(t)$ is an adjustment for the timing of the an-

[1] Other approaches include vector auto-regression (VAR) studies such as Christiano, Eichenbaum, and Evans (1999) and Bernanke, Boivin, and Eliasz (2005), and narrative approach by Romer and Romer (2004).

[2] Federal funds futures have traded at the Chicago Board of Trade exchange since October 1988. Tight window is defined as ten minutes before the announcement and twenties minutes after the announcement. Wide time window is defined as fifteen minutes before the announcement and forty five minutes after the announcement. The changes in prices are adjusted for the timing of the announcement within the month, which accounts for the fact that fed funds futures pay out based on the average effective rate over the month.

nouncement within the month.[3] We focus on a window of Δ_{-} = ten minutes before the announcement and Δ_{+} = twenty minutes after the announcement. The high-frequency shock series begins in January 1995 and ends in December 2018. I then aggregate the high-frequency shocks to quarter-level following Ottonello and Winberry (2020).[4] Summary statistics of monetary policy shocks can be found in Table 1 Panel A. There are 200 daily shocks with a mean of approximately zero and a standard deviation of 6bp. The quarterly "smoothed" shocks have similar features to the original high-frequency shocks. Panel A also include the summary statistics of policy news shock of Nakamura and Steinsson (2018). Figure 1 plots both the daily and quarterly measured monetary shocks.

[Figure 1 Here]

[Table 1 Panel A Here]

2.1.2 Forecast Error

The primary variable of interest that determines the heterogeneous investment sensitivities is firm's earnings forecast error, which is defined as the difference between the realized earnings and their forecast values. The main measure is the manager's forecast error on firms' earnings in the next fiscal year. I use manager's forecasts on the coming fiscal year end earnings per share (EPS) from IBES Guidance dataset. US firms with non-missing IBES permanent ticker and US dollars guidance are considered. The sample is from 2003 to 2018. If the guidance is a range, average is taken. Observations are dropped if their earnings estimate end month and announcement month are different. If there are more than one announcement within a year, then the last available announcement in that year is taken.

The forecast error is defined as the scaled difference between the realized earning and its forecast value.

$$\text{Forecast Error}_{i,t} = \frac{2(\text{Earning}_{i,t} - \mathbb{E}^{\theta}_{t-1}\text{Earning}_{i,t})}{|\text{Earning}_{i,t}| + |\mathbb{E}^{\theta}_{t-1}\text{Earning}_{i,t}|} \tag{2}$$

The forecast errors that are above 100% or below -100% are dropped. Forecast errors of negative earnings are dropped.

The additional measure of forecast errors using analyst's median consensus forecasts of

[3] This adjustment accounts for the fact that Fed Funds Futures pay out based on the average effective rate over the month. It is defined as $\tau(t)\tau^{n}_{m}(t) - \tau^{d}_{m}(t)$, where $\tau^{d}_{m}(t)$ denotes the day of the meeting in the month and $\tau^{n}_{m}(t)$ the number of days in the month.

[4] They construct a moving average of the raw shocks weighted by the number of days in the quarter after the shock occurs. They weight shocks by the amount of time firms have had to react to them.

firms' long-term earning growth (expected annual increase in operating earnings over the company's next three to five years) is considered as a robustness check. Details about construction of long-term earning growth forecast errors can be found in the Appendix A.[5] Summary statistics of forecast errors can be found in Table 1 Panel B. Forecast errors are measured at the annual frequency. Manager's earning forecast in the sample has a mean of 0.05 and a volatility of 26%. Forecast error of long-term earning growth is centered around zero, with a volatility of 21.6%. The distribution of manager and analyst's forecast errors are shown in Figure 2.

[Figure 2 Here]

[Table 1 Panel B Here]

2.1.3 Investment

I use perpetual inventory method to compute firm-level physical and customer capital stock at the quarter frequency with reasonable assumptions on the initial values k_0 and depreciation rates:

$$k_{t+1} = (1 - \delta)k_t + i_t \tag{3}$$

The firm-level measure of investment is defined as log-differences in capital: $\Delta log k_{i,t+1}$, where $k_{i,t+1}$ is the book value of the physical or customer capital stock of firm i at the end of period t.

Summary statistics of investment and real sales growth are presented in Table 1 Panel C. The average change in physical capital stock is 0.017, with a standard deviation of 0.072. The average change in customer capital stock is 0.026, with a standard deviation of 0.035. The average real sales growth is 1.5 percentage and its standard deviation is 17.9 percentage. A correlation matrix of firm characteristics is shown in Table 2. Forecast error has low correlation with other firm characteristics such as leverage, liquidity, past sales growth, age and intangibility.

[Table 2 Here]

[Table 1 Panel C Here]

[5] To avoid look-ahead bias in the empirical test, I use model implied realized earning instead of realized earning when computing the forecast errors.

2.1.4 Other Variables and Sample Construction

The other firm characteristics I use in the baseline regression specification include leverage, size, liquidity, current asset ratio, past sales growth and a dummy for dividend payer. The aggregate variables used in the empirical test include price deflator, GDP growth, inflation rate, unemployment rate as well as their Greenbook forecasts and forecast revisions. After merging forecast errors from IBES, aggregate variables and firm-level variables from Compustat, I drop firms not incorporated in the United States and firm-quarter observations with negative or missing sales, negative liquidity and small firms with gross capital less than 5 millions. Firms in finance and utility sectors, as well as nonoperating establishments and industrial conglomerates are not included. Firms with investment spell less than three years are dropped to mitigate the impact of assumed initial values. The final sample covers periods from 2003 to 2018.[6] More details of the sample and variables construction can be found in the Appendix A.

2.2 Predictable Forecast Error

To begin, I assess whether firms extrapolate when they form earnings forecast and if so, whether expectations of firm earnings overreact to current conditions or underreact? Following Bordalo et al., (2021), I regress next year's firm-level forecast errors on current-year firm-level financial outcomes. Under rational expectations, the manager's forecast errors should be unpredictable based on any information available to the firm when forecast is made. However, if beliefs about the firm's earnings overreact, displaying overoptimism during good times and undue pessimism during bad times, then future forecast errors should be negatively predicted by current firm-level fundamentals.

I perform the following regression test at the annual frequency:

$$\text{Forecast Error}_{i,t} = \alpha_i + \alpha_t + \beta X_{i,t-1} + \epsilon_{i,t} \tag{4}$$

where $X_{i,t-1}$ is firm-level earning forecast, investment and profit in the last period. Each specification includes firm and year fixed effects. Table 3 Panel A reports the results of manager's forecast error. In column (1), we see that firms making high forecasts of earnings for next year have lower earning forecast errors on average. In column (2), firms investing more to-

[6] The final sample goes from 2003 to 2018 for manager's forecast errors and it goes from 1995 to 2018 for analyst's forecast errors.

day give overly optimistic forecasts. In column (3), firms with higher profits today are, on average, more disappointed next year. A one standard deviation higher firm investment rate, about 20% higher, is on average associated with $20\% \times 0.070 \approx 1.4\%$ stronger disappointment in earnings next year (compared with a 4.4% average forecast error). The evidence on manager's beliefs is consistent with belief overreaction documented by Gennaioli et al., (2016), Barrero (2020) and Bordalo et al., (2021).

In panel B, I show the coefficients from the Coibion and Corodnichenko (2015) regressions for long-term earning growth using I/B/E/S "street earnings" instead of GAAP earnings from Compustat. The negative significant coefficient estimates indicate that long-term earnings expectations are very extrapolative and exhibit some degree of overreaction.

[Table 3 Here]

2.3 Heterogeneous Responses to Monetary Shocks

2.3.1 Main Results: Investments and Sales Growth

I estimate the following baseline empirical specification

$$\begin{aligned}\Delta log y_{i,t+1} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t+1}\end{aligned} \tag{5}$$

where $y_{i,t+1}$ is firm's physical capital stock, customer capital stock or real sales. α_i is a firm i fixed effect, $\alpha_{s,t}$ is a sector s by quarter t fixed effect, ϵ_t^m is the quarterly monetary policy shock, Forecast Error$_{i,t-1}$ is the standardized firm's forecast error [7] and $Z_{i,t-1}$ is a vector of controls including size, leverage, liquidity, past sales growth, market-to-book ratio, and a dummy for dividend payout. To control for differences in cyclical sensitivities across firms, I also include the interaction of forecast error with the previous quarter's GDP growth. The main coefficient of interest is β, which measures how the semi-elasticity of $\Delta log y_{i,t+1}$ with respect to monetary shocks ϵ_t^m depends on the within-firm variation in forecast errors. I cluster standard errors two ways to account for correlation within firms and within quarters.

Table 4 reports the results from estimating the baseline specification in equation (5). Panel A presents the results using manager's forecast error. The first three columns in Table 4 show

[7] Standardized forecast error is $\frac{\text{Forecast Error}_{i,t-1} - E(\text{Forecast Error}_{i,t-1})}{\sigma(\text{Forecast Error}_{i,t-1})}$, where $E(\text{Forecast Error}_{i,t-1})$ is the average value of Forecast Error$_{i,t-1}$ and $\sigma(\text{Forecast Error}_{i,t-1})$ is the standard deviation of Forecast Error$_{i,t-1}$ over the sample.

that firms with higher forecast error (overpessimistic) are more responsive to monetary shocks in physical capital investment. Column (1) implies that a firm has approximately a 0.95% further reduction in physical capital investment (0.95 units lower semi-elasticity of investment) following a contractionary monetary policy when it is one standard deviation higher in forecast error than it typically is in this sample. Adding firm-level controls $Z_{i,t-1}$ in Column (2) does not significantly change this point estimate; therefore, I focus on specifications with firm-level controls $Z_{i,t-1}$ for the remainder of the paper. Column (3) removes the sector-by-quarter fixed effects in order to estimate the average effect of a monetary shock on physical capital investment.[8] A 1% increase in interest rate reduces physical capital investment, on average, by 1.01% (average physical capital investment semi-elasticity). Therefore, the interaction coefficients in the previous columns imply an economically meaningful degree of heterogeneity.

Column (4) to (6) report the results for customer capital investment. Column (5) shows that a firm has approximately 0.56% further reduction in customer capital investment to contractionary monetary policy when it is one standard deviation higher in forecast error. This point estimate is closed to 0.47% in column (4) without adding firm controls. On average, a 1% increase in interest rate reduces customer capital investment by -0.62%. Column (7) to (9) shows the results for real sales growth. On average, firm's real sales growth increased by 1.91% when interest rate goes up by 1% but statistically insignificant, while an overpessimistic firm with one standard deviation higher in forecast error is 4.55% lower in the quarter sales growth.

[Table 4 Here]

Panel B reports the results of the baseline empirical test using analyst's forecast errors. Column (2) (5) and (8) implies that firm has an approximately 1.21%, 0.36% and -2.09% reduction in physical capital investment, customer capital investment and real sales growth, respectively, when it is one standard deviation higher in forecast error.

Table 5 repeat the same exercises as that in Table 4 using a dummy variable for extrapolation bias. The dummy takes value one when firm is overpessimistic, i.e, the forecast error is positive, and zero otherwise. The conclusion implied from Table 5 is consistent with that from Table 4.

[8]

$$\begin{aligned}\Delta log y_{i,t+1} = \alpha_i + \alpha_{s,q} + \delta\epsilon_t^m + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{i,t-1} + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}\end{aligned} \tag{6}$$

where α_{sq} is a sector s by quarter q seasonal fixed effect and Y_t is a vector with four lags of GDP growth, the inflation rate and the unemployment rate.

[Table 5 Here]

2.3.2 Dynamics

Monetary policy shocks have significant differential effects on corporate investment, but is the heterogeneity large and persistent? I then estimate the dynamics of these differential responses across firms using Jorda (2005)-style local projection of specification in equation (7):

$$\begin{aligned}\Delta y_{i,t+h} = \alpha_i + \alpha_{s,q} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma_1' Z_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{7}$$

where $h \geq 1$ indexes the regression horizon. The coefficient β_h measures how the cumulative response of corporate investments and real sales growth in quarter $t+h$ to a monetary shock in quarter t depends on the firm's forecast errors about future earning opportunities in quarter $t-1$. Figure 3 panel (a) (b) and (c) reports the coefficient β_h estimates of the baseline specification over quarters h for physical capital investment, customer capital investment and real sales growth. The heterogeneity in investment is large and persistent for up to three years.[9]

[Figure 3 Here]

2.4 Industry Heterogeneity

At the industry-level, I provide further evidence linking this heterogeneity by forecast errors to customer capital by showing that the differences among firms are sizable in industries with high advertising intensity and negligible in those with minimal advertising intensity.

Compustat variable XAD has lots of missing values. Following Belo, Gala, Salomao and Vitorino (2021), I treat the missing XAD data as follows. Staring from 1972, I impute missing advertising data based on the observed Selling, General and Administrative (SG&A) expenses using the firm-level average ratio of advertising expenses-to-SG&A ratio for the years in which neither of these values is missing. Given the different disclosure requirements throughout the years, however, I cap the imputed amount at 1% of sales for the years from 1972 through 1993 (to make the imputed values consistent with the reporting standards). I exclude from the sample all the firms with missing XAD during the entire sample period.

[9] These long-run differences, however, are imprecisely estimated with large standard errors

I first compute a time-series average of industry advertising intensity at the 2-digit SIC level.[10] I calculate firm-level ratio of advertising expenditure to sales: $\frac{\text{XAD}}{\text{SALES}}$, take the weighted average of this ratio by sales within each defined industry and average over time. I then sort industries into two groups based on this measure: above and below median. The industries falling into our high and low advertising expense samples are given in Tables A.1 and A.2 in Appendix A.

I repeat the main analysis over these two subsamples. Table 6 shows that results of baseline test over industries with different advertising intensity. The main results remain negatively significant and stronger in advertising intensive industry. Compared to the estimates in full sample, the magnitude of coefficient estimates in advertising-intensive industry are 46%, 14% and 54% larger for physical capital investment, customer capital investment and real sales growth, respectively, for manager's forecast errors. They are 16%, 19% and 40% for analyst's forecast errors. They become insignificant in the industries with low advertising intensity.

[Table 6 Here]

2.5 Additional Results

In the Appendix D, I perform four sets of robustness checks. I first check the robustness regarding firm-level heterogeneity. To confirm that extrapolation bias did drive the heterogeneity in investment sensitivities, I further control for interactions of monetary shocks with other firm-level covariates such as past sales growth, size, leverage, liquidity and intangibility. Results can be found in section D.1 Table A.3 and A.4. It suggests that the differential responses in investment by forecast errors are not driven by firms' heterogeneous financial or liquidity positions.

The second set of results repeat the same exercises in the main analysis but using different measures of monetary shocks including raw changes in fed funds rates and policy news shocks from Nakamura and Steinsson (2018). Table A.5 reports the results using fed funds rates and policy news shock from Nakamura and Steinsson (2018), respectively.

I also verify that the main results are robust to different assumed values of customer capital depreciation rate. In Table A.7, the coefficient estimates for customer capital investment remain statistically and economically significant when the assumed annual depreciation rate varies between 0.15 and 0.3, although the economic magnitude is increasing in the depreciation rate.

[10]Compustat item XAD is only available at the annual frequency.

In the last set of results, I show that the heterogeneous investment sensitivities are not driven by business cycle effects, as the coefficient estimates of the interaction of previous forecast error and the current GDP growth are mostly insignificant. The results can be found in Table A.8.

[Table A.3 A.4 A.5 A.7 and A.8 Here]

3 Model

The model builds on Gourio and Rudanko (2014) where customer acquisition is considered in a frictional product market and the search friction generates long-term customer relationships. I extend this search theoretic model of firm dynamics by adding extrapolative expectation and incorporating it into a New Keynesian framework, which consists of intermediate retailers, a final good producer and a monetary authority. I model firm's production, hiring and customer acquisition decisions in a separate production sector to isolate the price rigidity from corporate decisions.

3.1 Producers

Time is discrete and infinite. There is a fixed unit mass of firms $j \in (0, 1)$ and each produces an undifferentiated good $y_{j,t}$ using a constant return to scale production function. For each firm, the output is sold to a corresponding retailer at an economy-wide wholesale price p_t.

3.1.1 Technology and Investment

Firm has a constant return to scale production technology $y_{j,t} = z_{j,t}k_{j,t}^{\alpha}$, where $k_{j,t}$ is the firm's physical capital stock, $l_{j,t}$ is the firm's production labor input and $z_{j,t}$ is an idiosyncratic productivity shock that follows a log-AR(1) process,

$$logz_{j,t+1} = \rho_z logz_{j,t} + \epsilon_{j,t+1} \tag{8}$$

where $\epsilon_{j,t+1} \sim N(0, \sigma^2)$.

Firm's output (scale) depends not just on its production technology, but also the size of its customer base, which is

$$y_{j,t} = min\{z_{j,t}k_{j,t}^{\alpha}, m_{j,t} + \mathbb{M}(b_{j,t}, s_{j,t})\} \tag{9}$$

where $m_{j,t}$ is firm j's existing customer base and $\mathbb{M}(b_{j,t}, s_{j,t})$ is a matching function in the product market that describes firm's new customer acquisitions. The details of frictions in the matching process will be discussed below.

Firm rents physical capital from household and faces a rental cost of $r_t + \delta$ every period, where δ is the physical capital depreciation rate.

3.1.2 Extrapolative Expectation

Firm make optimal corporate decisions under subjective expectations, which are assumed to be extrapolative. The formalization of non-rational beliefs is based on extrapolative expectation from Bordalo, Gennaioli, and Shleifer (2018)[11], which builds on the representativeness heuristic from Kahneman and Tversky (1972). The true distribution is Markovian, denoted by $f(X_{t+1}|X_t)$, and stored in the agent's memory. Under extrapolative expectation, the agent's beliefs follow the distorted distribution:

$$f^{\nu}(X_{t+1}|X_t) \propto f(X_{t+1}|X_t)\left[\frac{f(X_{t+1}|X_t)}{f(X_{t+1}|\mathbb{E}_{t-1}(X_t))}\right]^{\nu} \tag{10}$$

The likelihood ratio measures the diagnosticity of outcome X_{t+1} on the basis of news at t, namely the increase in its probability relative to the case of neutral news $X_t = \mathbb{E}_{t-1}(X_t)$. ν captures the extent to which memory focuses on such extrapolative outcomes. $\nu = 0$ reduces to the rational expectations.

When firm's productivity process is given by equation (8), at time $t-1$ the extrapolative manager perceives next period productivity to be a Gaussian process following:

$$logz_t|(logz_{t-1}, \epsilon_{t-1}) \sim \mathbb{N}_t(\rho_z(logz_{t-1} + \nu\epsilon_{t-1}), \sigma_z^2) \tag{11}$$

where $\nu > 0$ governs the degree of overreaction to the information received in the last period. Good news $\epsilon_{t-1} > 0$ make extrapolative expectation too optimistic (i.e $\mathbb{E}^{\nu}_{t-1}(logz_t)$ is too high compared with $\mathbb{E}_{t-1}(logz_t)$ under rational expectation), and bad news $\epsilon_{t-1} < 0$ make extrapolative expectation too pessimistic.

[11] It is called "Diagnostic Expectation" in Bordalo, Gennaioli, and Shleifer (2018)

3.1.3 Frictional Product Market and Customer Acquisition

Firms hire sales people to acquire new customers. They are placed in separate sales locations and generate s efficiency unites of sales people from an increasing and convex function $\kappa(s)$. The measure L^b household members engaged in buying activity have idiosyncratic differences in tastes over different goods. Product market frictions imply that household member must meet with the firm's sales person to determine whether he or she is willing to buy a particular firm's good. Here I assume that buyers decide on the sales locations to visit independently and that sales people have finite capacity to handle potential buyers.

Meetings between sales people and potential buyers are thus subject to coordination frictions in the search market; each period some sales locations go without any potential buyers arriving, while others get more than the sales person can handle. Following Gourio and Rudanko (2014), this friction in new customer acquisition is captured by a firm-level direct search matching function. When s efficiency units of sales people meet with b units of potential buyers arriving across sales locations, they form a measure of new customer relationships:

$$\mathbb{M}(b_{j,t}, s_{j,t}) = \xi \left(b_{j,t}^{\gamma_m} s_{j,t}^{1-\gamma_m} \right)^{\eta} \tag{12}$$

where $\xi > 0$ measures the average matching efficiency, $\gamma_m \in (0, 1)$ measures the matching function elasticity and $\eta > 0$ governs the return to scale of this matching technology.[12]

I use $\theta = b/s$ to denote the firm-specific average queue-length of potential buyers across a firm's sales people. The probability of matching per sales person, $\frac{\mathbb{M}(b,s)}{s} = \eta(\theta, s) = \xi\theta^{\gamma_m\eta} s^{\eta-1}$, is an increasing function of the queue length. Similarly, the probability of matching per potential buyer, $\frac{\mathbb{M}(b,s)}{b} = \mu(\theta, s) = \xi\theta^{\gamma_m\eta-1} s^{\eta-1}$, is a decreasing function of the queue length.[13]

To capture the fact that customers may walk away, I assume that the existing relationships end with probability δ_n each period. Therefore, the customer capital follows:

$$m_{j,t+1} = (1 - \delta_n)(m_{j,t} + \mathbb{M}(b_{j,t}, s_{j,t})) \tag{13}$$

To allow firms influence over customer acquisition through their pricing decisions, I assume firms can commit to an initial discount $\varsigma_{j,t}$, which they use to compete for new cus-

[12] This measure is a product of the exogenous probability of a meeting leading to a new customer relationship, and the measure of meetings taking place.

[13] $\eta(\theta, s) = \mu(\theta, s)\theta$. These expressions capture the idea that an increase in potential buyers per sales person increases matches per sales person but at a diminishing rate because these buyers are more likely to arrive in locations with sales people occupied.

tomers. The household member has no difference in choosing between working as production worker or searching as buyer each period, so their break even condition implies that:

Proposition 1. $w = \mathbb{max}_{(\varsigma,\theta)}\mu(\theta, s)\varsigma$, *i.e, the marginal benefit of searching as a worker, which is the expected discount he/she can receive* $\mu(\theta)\varsigma$*, should be equal to the opportunity cost, which is receiving a wage rate when working as a production worker.*

In equilibrium, different firms indeed offer different discounts, depending on their desire to expand sales.[14]

3.1.4 Firm Financing

Firm finances its corporate investments using either internal funds or new equity issues. Equity financing is costly, which is modeled as linear equity issuance costs and is captured by λ. Let $d_{j,t}$ denotes the dividend payouts and equity issuance is modeled as negative dividends payout. The total issuance costs are given by $\lambda d_{j,t}\mathbb{1}(d_{j,t} < 0)$. It follows that the firm's budget constraint can be written as

$$d_{j,t} = p_t y_{j,t} - s_{j,t}\eta(\theta, s)\varsigma_{j,t} - (r_t + \delta)k_{j,t} - w_t\left(\frac{\kappa}{2}s_{j,t}^2 + oc\right) \tag{14}$$

where oc is the labor overhead cost and $\frac{\kappa}{2}s_{j,t}^2$ functions as the adjustment cost of recruiting sales person.

3.1.5 Firm Recursive Optimization Problem

The original equity value of the firm, $v(z, z_{-1}, m, k)$, is defined as the sum of all discounted future dividends, where the state variables $S = (z, z_{-1}, m, k)$ consists of current and lagged productivity, customer capital, and physical capital.

Every period, the firm chooses the number of sales people $s_{j,t}$ to recruit, the amount of initial discount $\varsigma_{j,t}$ it offers to attract new customers, physical investment $i_{j,t}$ and output $y_{j,t}$ it

[14]In practice, I assume that the customer depreciation rate is large enough to guarantee that the firm hires some sales people each period, even when a low productivity realization causes it to contract overall.

produces to maximize its recursive value function:

$$
\begin{aligned}
v_t(z, z_{-1}, m, k) =& max_{y,s,\varsigma,i} \;\; d + \lambda d \mathbb{1}(d < 0) + \beta \mathbb{E}^{\nu}{}_t v_{t+1}(z', z, m', k') \\
d =& p_t y - s\eta(\theta, s)\varsigma - (r_t + \delta)k - w_t \left(\frac{\kappa}{2} s^2 + oc \right) \\
y \leq& m + \xi s \eta(\theta, s) \\
y \leq& z k^{\alpha} \\
m' =& (1 - \delta_n)(m + \xi s \eta(\theta, s)) \\
log(z') =& \rho_z log(z) + \epsilon_z
\end{aligned}
\tag{15}
$$

with $\mu(\theta, s)\varsigma = w_t$ and $log(z)$ is AR(1) process. All choice variables are non-negative.

Proposition 2. *The firm's optimal conditions imply*

1. $\theta = \frac{\gamma_m}{1-\gamma_m} \kappa s$
2. $\varsigma = \frac{w}{\xi} \left(\frac{1-\gamma_m}{\gamma_m \kappa} \right)^{1-\eta} \theta^{2-\eta-\gamma_m \eta}$

3.2 Representative Household

There is a unit measure continuum of identical households with preferences over consumption C_t and total labor supply: doing market work L_t^m or searching as buyers L_t^b in the product market, whose expected utility is as follows:

$$
\sum_{t=0}^{\infty} \beta^t (logC_t - \Psi(L_t^b + L_t^m))
$$

subject to the budget constraint:

$$
P_t C_t + \frac{B_{t+1}^{rf}}{R_t^{nom}} \leq W_t(L_t^b + L_t^m) + (R_t^{nom} + \delta)K_t + B_t^{rf} + T_t \tag{16}
$$

where β is the discount factor of households, Ψ is the disutility of working, P_t is the price index, R_t^{nom} is the nominal rate, W_t is the nominal wage rate, B_t^{rf} is the one-period risk free debt and T_t is the transfer from all firms including the nominal profits.

Every period, the households make decision on the allocation of one unit of time among leisure, market work and searching as a buyer in the product market, which determine the real wage in the following optimal condition:

$$w_t = -\frac{U_l(C_t, L_t^b + L_t^m)}{U_c(C_t, L_t^b + L_t^m)} = \Psi C_t \tag{17}$$

The decision over consumption and risk-free bonds determine the discount factor, which is linked to nominal rate and inflation rate through the Euler equations:

$$\Lambda_{t+1} = \frac{1}{R_t^{nom}/\Pi_{t+1}} \tag{18}$$

3.3 Model: New Keynesian Block

The New Keynesian block of the model consists of a final good producer who produces final goods, intermediate retailers who have price rigidity and a monetary authority who sets the interest rate rule. It generates: 1) a New Keynesian Phillips curve relating nominal variables to the real economy and 2) a Taylor Rule which links the monetary policy shock and inflation to the nominal interest rate.

Final good producer There is a representative final good producer who produces the final good Y_t using intermediate goods from all retailers with the production function:

$$Y_t = \left(\int \tilde{y}_{i,t}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}$$

where γ is the elasticity of substitution between intermediate goods. The final good producer's profit maximization problem gives the demand curve $\tilde{y}_{i,t} = \left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma} Y_t$ where the price index is $P_t = \left(\int \tilde{p}_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}$. The final good serves as the numeraire in the model.

Intermediate retailers There is a fixed mass of retailers $i \in (0, 1)$. Each retailer i produces a differentiated variety $\tilde{y}_{i,t}$ using the heterogeneous production firms' good as its only input: $\tilde{y}_{i,t} = y_{i,t}$, where $y_{i,t}$ is the amount of undifferentiated good demanded by retailer i.

The retailers are monopolistic competitors who set their prices $\tilde{p}_{i,t}$ subject to the demand curve generated by the final good producer and the wholesale price of the input P_t. Retailers pay a quadratic menu cost in term of final good $\frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$, to adjust their prices as in Rotemberg (1982), where Y_t is the final good. The resulting price stickiness comes from the price-setting decisions made by retailers maximizing profits.

$$\pi_{i,t} = (\tilde{p}_{i,t} - p_t)\tilde{y}_{i,t} - \frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$$

Proposition 3. *The retailer's profit maximization gives the following* ***New Keynesian Phillips curve****:*

$$log\Pi_t = \frac{\gamma - 1}{\psi} log\frac{p_t}{p*} + \beta \mathtt{E_t} log\Pi_{t+1} \tag{19}$$

where $p* = \frac{\gamma-1}{\gamma}$ *is the steady state wholesale price, or in other words the marginal cost for retailer firms.*

The Phillips Curve links the New Keynesian block to the production block through the relative real wholesale price $p*$ for production firms. If the expectation of future inflation is unchanged, when aggregate demand for the final good Y_t increases, retailers must increase production of their differentiated goods because of the nominal rigidity. This in turn increases demand for the production goods $y_{i,t}$, which raises the real wholesale price p_t and generates inflation through the Phillips curve.

Proposition 4. ***Inflation dynamics*** *follows*

$$\Pi_t = exp\left(\frac{1}{\psi_\pi}\left[log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right) - \epsilon_t^m\right]\right) \tag{20}$$

Monetary authority The monetary authority sets the nominal risk-free R_t^{nom} according to the log version of a Taylor rule:

$$log(R_t^{nom}) = log\frac{1}{\beta} + \psi_\pi log\Pi_t + \epsilon_t^m \tag{21}$$

where $\epsilon_t^m \sim N(0, \sigma_m^2)$, Π_t is gross inflation in the final good price and ψ_π is the weight on inflation in the reaction function. ϵ_t^m is the monetary policy shock.

3.4 Market Clearing Conditions

Consumption good market clears: the total of consumption, investment and cost of investment and financing should be equal to the total output in the economy.

$$C_t + EIC_t = Y_t \tag{22}$$

Labor market clears: the aggregate demand for labor, used in marketing and sales, should be equal to the aggregate labor supply from the household.

$$L^d = \int (\kappa(s(S)) + oc) d\phi(S) = L^m \tag{23}$$

Matching consistency: in the competitive search market, the total number of buyers should be equal to the total number of sales people.

$$L^s = \int s(S)\theta(S) d\phi(S) = L^b \tag{24}$$

Zero net supply of risk free bond

$$B^{rf} = 0 \tag{25}$$

3.5 Model Equilibrium

A stationary competitive search equilibrium specifies firm decision rules $y(S; w, p, r)$, $s(S; w, p, r)$, $\varsigma(S; w, p, r)$, $d(S; w, p, r)$ and the value function $v(S; w, p, r)$, household decision rules C, L^b, L^m, the stationary distribution $\nu(S)$ across firm producers and the equilibrium prices p, w, Π and r such that

- Household's decision rules and value function solve the problem
- Firms' decision rules and value function solve the problem
- Buyer satisfies $\mu(\theta, s)\epsilon = w$ and $\theta > 0$
- Stationary distribution $\phi(S') = T(\phi(S))$
- All the markets clear

4 Model Solution

4.1 Optimal Decisions

In this section, I characterize firm's optimal decisions and their related properties. For simplicity, I assume constant return to scale matching technology ($\eta = 1$) starting from this section.

Optimal decision about discount offering to new customer ς satisfies:

$$\frac{1}{\gamma}\varsigma = v_n(z, z_{-1}, m, k) \tag{26}$$

From the above two optimal conditions, it is clear that the productivity news that firm receives in the previous period affects physical capital investment and pricing strategy through changing marginal value of capitals. Firms that receive good news in the previous period, i.e, $\epsilon_{t-1} > 0$ become overoptimistic. In contrast, firms that receive bad news become overpessimistic and they underestimate their future profitability compared to firms under rational expectation. Everything else equals, overoptimistic firms have higher marginal revenue of capital so they are willing to offer more discount to attract more new customers.

$$v_i^{opt}(z, z_{-1}, m, k) > v_i^{pes}(z, z_{-1}, m, k) \tag{27}$$

where $i = k, n$ implies

$$\varsigma^{opt} > \varsigma^{pes} \text{ and } i^{opt} > i^{pes} \tag{28}$$

The optimal decision on marketing and selling expense (recruiting sales people) s suggests:

$$w_t \frac{\kappa'(s)}{\eta(\theta)} + \varsigma = v_n = p_t - (r_t + \delta)k_y + \beta(1 - \delta_n)\mathbb{E}_z^{\nu} v_n(z, z_{-1}, m, k) \tag{29}$$

The left hand side is the marginal cost of recruiting sales people, which consists of the wages of additional sales people and the discount. The right hand side is the marginal revenue, which is the sum of today's sales revenue and the continuation value of new customer, net of production cost. Combining with proposition 2, we can easily conclude that $s^{opt} > s^{pes}$.

Following a contractionary monetary policy, final good and labor demand decline and therefore, price of output and wage drop. From equation (29), on average, firms offer lower discount and invest less in both physical and customer capital following an interest rate hike. Firm size shrinks. Overpessimistic firms are more responsive to the shocks and they cut down investment more aggressively compared to firms on average since they underestimate their future profitability. This is how extrapolation bias generates differential responses across firms.

4.2 Calibration and Simulation

I study the model solutions and perform quantitative analysis by means of calibration and simulation. I start with an explanation of the quarterly calibration and simulation, followed by discussions on model mechanisms and optimal solution. I solve for the steady state equilibrium via value function iteration and do transition dynamics before simulation. Details on numerical algorithm are included in Appendix C.

The quarterly calibration is summarized in Table 9. I take parameter values reported in the literature whenever possible and choose the rest of them to match the data moments from the empirical sample. Parameters can be divided into four groups: firm producer (technology, investment and financing), extrapolative expectation, household's preference and the New Keynesian block.

Firm producer The first block of the table is related to firm producers in the model. I set the capital share $\alpha = 0.63$ as that in the literature. η is set to 1 to obtain constant return to scale matching technology. Matching function elasticity γ_m is set to match the ratio of buyers' time to sellers' time: 15% estimated using data from the Occupational Employment Statistics (OES) survey and the amount of time consumers spend on shopping from the American Time Use Survey (ATUS).[15] It also governs the extent to which it is profitable to offer low prices to attract more customers. Matching function coefficient ξ is set to 0.1 following Gourio and Rudanko (2014).

Physical capital depreciates at rate $\delta = 12\%$ per year, which is a standard assumption. Customer capital depreciates at rate $\delta_n = 20\%$ per year, which falls between 10% and 25% of intangible capital depreciation rate estimated in the literature. I calibrate the customer capital adjustment parameter κ to match $\frac{\text{XSGA-XRD-RDIP}}{\text{SALES}}$. COGS mainly covers the labor cost on production activities while XSGA includes the labor expenditure on intangible investment such as marketing and selling expense. Firm finance their investment through internal funds and costly equity issuance. Variable issuance costs λ is set to match new equity issuance-to-lagged total asset ratio.

Persistence ρ_z and conditional volatility σ_z of the idiosyncratic firm productivity shock are calibrated to match the auto-correlation and cross-sectional dispersion of profitability. ν governs the degree of extrapolation and it is calibrated to match the correlation between profitability and forecast error.

Household's preference For the calibration of household's preference, the discount factor β

[15] Gourio and Rudanko (2014) shows the details of estimating buyers' and sellers' time.

is set to be 0.99, which implies a 4% annual real rate, which is standard in the literature. I choose the disutility of labor supply Ψ to generate a steady state employment of 1.

New Keynesian Block Following Ottonello and Winberry (2020), I set the elasticity of substitution over intermediate goods γ to be 10, implying a steady state markup of 11%. I set the Rotemberg (1982) price adjustment cost $\varphi = 90$ to generate a Phillips Curve slope equal to 0.1 and φ_π, the weight on inflation in the reaction function, to be 1.25, in the middle of the range commonly considered in the literature.

[Table 9 Here]

Simulation The empirical targets are based on the longer sample set I use for the empirical evidence above: quarterly Compustat data from 1995Q1 to 2018Q4. To compute the corresponding firm-level moments from the calibrated model, I simulate a panel of 10,000 firms for 200 quarters in total, including a 100-quarter burn-in period. I simulate 50 artificial samples and report the cross-sample average results as model moments in Table 10. It shows cross-simulation averages of standard deviation of profitability, auto-correlation of profitability, average equity issuance-to-total asset ratio, correlation between forecast errors and profitability, as well as the ratio of (XSGA-XRD-RDIP) to SALES.

[Table 10 Here]

5 Quantitative Analysis

I now quantitatively analyze the effect of a monetary shock ϵ_t^m. The heterogeneous effects of monetary policy on firms' investment are consistent with the empirical results from the baseline analysis. The economy is initially at the steady state and unexpectedly receives a $\epsilon_0^m = 0.0025$ innovation to the Taylor rule which reverts to 0 according to $\epsilon_{t+1}^m = \rho_m \epsilon_t^m$ with $\rho_m = 0.5$. I compute the perfect foresight transition path of the economy as it converges back to the steady state.

To compare our model to the data, I simulate a panel of 5,000 firms in response to a monetary shock and estimate the baseline empirical specification on the simulated data.[16] I assume that the high-frequency shocks ϵ_t^m that we measure in the data are innovations to the Taylor rule in the model. I estimate the regressions using data from one year before the shock to twenty quarters after the shock.

[16] In the model, I use time fixed effect rather than sector-time fixed effect because the model does not contain multiple sectors. In addition, I do not include the subset of control variables $Z_{i,t-1}$ which are outside the model.

5.1 Model Implied Differential Investment Sensitivities

To compare the model to the data, I estimate the baseline specification on the simulated data using scaled earning forecast error defined as

$$\frac{2(z_t k_t^{\alpha} - \mathbb{E}_{t-1}^{\nu} z_t k_t^{\alpha})}{|z_t k_t^{\alpha}| + |\mathbb{E}_{t-1}^{\nu} z_t k_t^{\alpha}|} \tag{30}$$

as a measure of firm-level extrapolation bias. The panel regression results for corporate investment are shown in Table 11. Columns (1) and (2) shows that overpessimistic firms are more responsive to monetary policy in the model. A firm with one standard deviation higher in forecast error has an approximately 3.99 percentage points lower in the physical investment semielasticity and 0.36 percentage points lower in the customer capital investment semielasticity than the average firm. Figure 4 plots the curves of marginal cost and marginal revenue for overpessimistic and overoptimistic firms before and after the shock. Product market friction and financial friction generate an upward sloping marginal cost curve while overoptimistic firms have higher marginal revenue of capital than overpessimistic firms. Therefore, overpessimistic firms have larger investment sensitivities to monetary policy.

5.2 Differential Pass-through

Contractionary monetary policy reduces the cost of production, which is the wage expense in this model. Firms have different pass-through of lower production cost to lower revenue in response to monetary shocks. In this section, I examine the channel of heterogeneous pass-through that is associated with the differential responses in corporate investments across firms both in the data and in the model.

Empirically, I follow the literature to measure firm-level profit margin as a proxy for "markup".[17] As discussed by De Loecker and Eeckhout (2017), within a particular industry, the ratio of revenue to cost of goods sold is a correct measure of firm-level markups, up to an industry-specific constant. Specifically, here I assume that firms within the same 3-digit industry-year have a common output elasticity so firm-level log profit margin ("markup") in deviation from the industry-year mean do not depend on the estimate of output elasticity. I first demean the firm-level profit margin at the industry-year level and then take the log-

[17] Hall (1986,1988), De Loecker and Warzynski (2012), De Loecker and Eeckhout (2017), Crouzet and Eberly (2018) and Gutierrez and Philippon (2018)

differences.[18] I consider three measures of profit margin in the data: $\frac{\text{SALES}}{\text{COGS}}$, $\frac{\text{SALES}}{\text{COGS + XSGA}}$ and $\frac{\text{SALES}}{\text{COGS + (XSGA - XRD -RDIP)}}$. Profit margin is winsorized at the 5^{th} and 95^{th} percentiles.

In the model, firm-level profit margin ("markup") is defined as $\frac{p_t y_{i,t} - s_{i,t}\eta(\theta_{i,t})\varsigma_{i,t}}{(r_t+\delta)k_{i,t}}$. Firms face a decline in output price p_t and an increase in rental rate r_t after a tightening of monetary policy. However, their responses in discount offering $\varsigma_{i,t}$ and capital demand $k_{i,t}$ are different. As is shown in Table 7, overpessimistic firms have higher pass-through of lower cost to lower revenue, as their profit margins drop more than firms on average. Specifically, the growth rate of profit margins has additional 1.48% to 1.94% reduction when firm is one standard deviation higher in its manager's forecast error. The estimate varies between 0.64% to 0.88% for analyst's forecast error.

5.3 Aggregate Implications: Role of Extrapolation Bias

Firm-level heterogeneous pass-through and investment adjustment establish a need to evaluate the allocative efficiency of monetary easing and its welfare effect. Previous literature emphasizes the role of financial frictions in the transmission of monetary policy to the aggregate economy but less discussions are conducted in the setup of frictional product market. Therefore, the role of extrapolation bias in the transmission of monetary policy through product market is studied in this section. Although we observe overreaction in corporate decisions at the firm level, however, whether the extrapolation bias has an amplification effect at the aggregate level remains unknown.

In the following quantitative exercise, I analyze the role of extrapolation bias in evaluating the effectiveness of expansionary monetary policy to the aggregate economy in the frictional product market. The impulse response functions of aggregate productivity following a 25 basis points interest rate cut are plotted in Figure 6. In addition, the impulse response function in the economy where agents have rational expectation are included for comparison. As it is shown in the Figure 6, expansionary monetary policy boosts the aggregate productivity when firms form extrapolative expectation over their earnings, while a model where firms are assumed to be rational fails to fit what we observe in the data. There is a hump-shape response in the aggregate productivity, output, consumption and capital to monetary shock. The aggregate effects of monetary policy are significantly larger with extrapolative expectation: with rational expectation, the increase in aggregate output is underestimated by 57%.

[18]The main results are not affected by the critique in Bond et al. (2020) of estimating output elasticities from revenue data.

6 Sensitivity Analysis

How does the quantitative effect of extrapolation bias depend on model parameters? In this section, I perform the sensitivity analysis of the aggregate results to different values of parameters that govern the process of new customer acquisition: matching function elasticity $\gamma_m \in (0.15, 0.2)$, matching function coefficient $\xi \in (0.1, 0.2)$ (hence different targets of buying and selling time), adjustment cost of recruiting sales people $\kappa \in (1, 4)$ and return-to-scale matching technology $\eta \in (1, 1.5)$. Table 12 shows the target moments: $\frac{\text{XSGA-XRD-RDIP}}{\text{SALES}}$, correlation between profitability and forecast errors, $\frac{\text{Equity}}{\text{Total Asset}}$, standard deviation and auto-correlation of profitability computed from models with different parameter values. $\frac{\text{XSGA-XRD-RDIP}}{\text{SALES}}$ is very sensitive to the span-of-control of matching technology. By allowing for the scalability of intangible capital, the ratio of intangible expenditure to sales and equity to total asset increase dramatically. The correlation of profitability and forecast errors are sensitive to the changes in all these four parameters while equity issuance is largely affected by η, κ and ξ. These four parameters do not affect moments of profitability that much.

The impulse response functions of aggregate productivity, output, consumption and capital for each numerical experiment are plotted in Figure 7 and 8. Allowing for the scalability of intangible capital greatly raise the aggregate impact of monetary easing. Lower adjustment cost of recruiting sales people κ and higher matching coefficient ξ also boost the effect of expansionary monetary policy. However, the effects of matching function elasticity γ_m on aggregate productivity and other variables are different. Higher γ_m reduces the allocative efficiency of monetary easing but increases the transmission of monetary easing to aggregate output and capital.

7 Conclusion

In this paper, I have argued that extrapolation bias amplifies the effect of monetary policy on allocation efficiency and aggregate output. I first showed that, in the data, overpessimistic firms with relatively low earning forecasts are more responsive in their physical and customer capital investment following a monetary policy shock. The fact that extrapolation bias drives these heterogeneous responses is in particular strong in advertising intensive industry. Second, I explain these facts in a heterogeneous firm New Keynesian model with dynamic directed search where firms make physical investment and customer acquisition through optimal pricing strategy. The aggregate effect of monetary policy is primarily driven by these overpessimistic firms.

Our results may be of independent interest to policymakers who are concerned about the redistribution effect of monetary policy across firms in a world where firms have extrapolation bias when forming earning forecasts. The model suggests that extrapolative expectation generates improved allocation efficiency following a monetary easing of 25 basis points interest rate cut.

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Figures

Figure 1: Monetary Shocks

This figure plots the monetary shocks at the daily and quarterly frequency. The red dash line represents the main measure of monetary shocks used in the baseline analysis: changes in Fed Funds future prices around FOMC announcements. The blue solid line represents the policy news shocks from Nakamura and Steinsson (2018). The sample covers periods from 1990Q2 to 2018Q4.

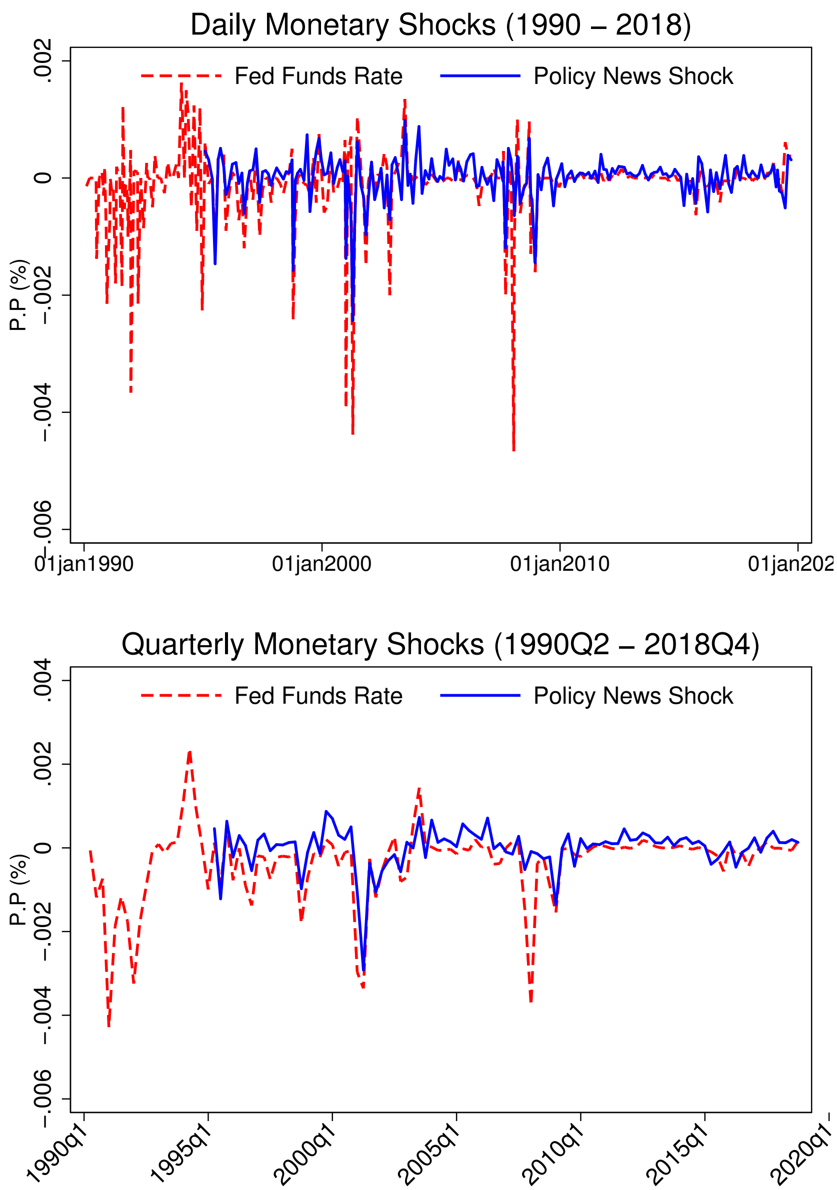


Figure 2: Forecast error of long-term earning growth and its model estimate

This figure plots the managerial short-term earning forecast error (top) and analyst's long-term earning growth forecast error (bottom left) as well as its reduced-form model estimate (bottom right, the red one). The sample covers periods from 1995Q1 to 2018Q4 for analyst's forecast error and covers periods from 2003Q1 to 2018Q4 for manager's forecast error.

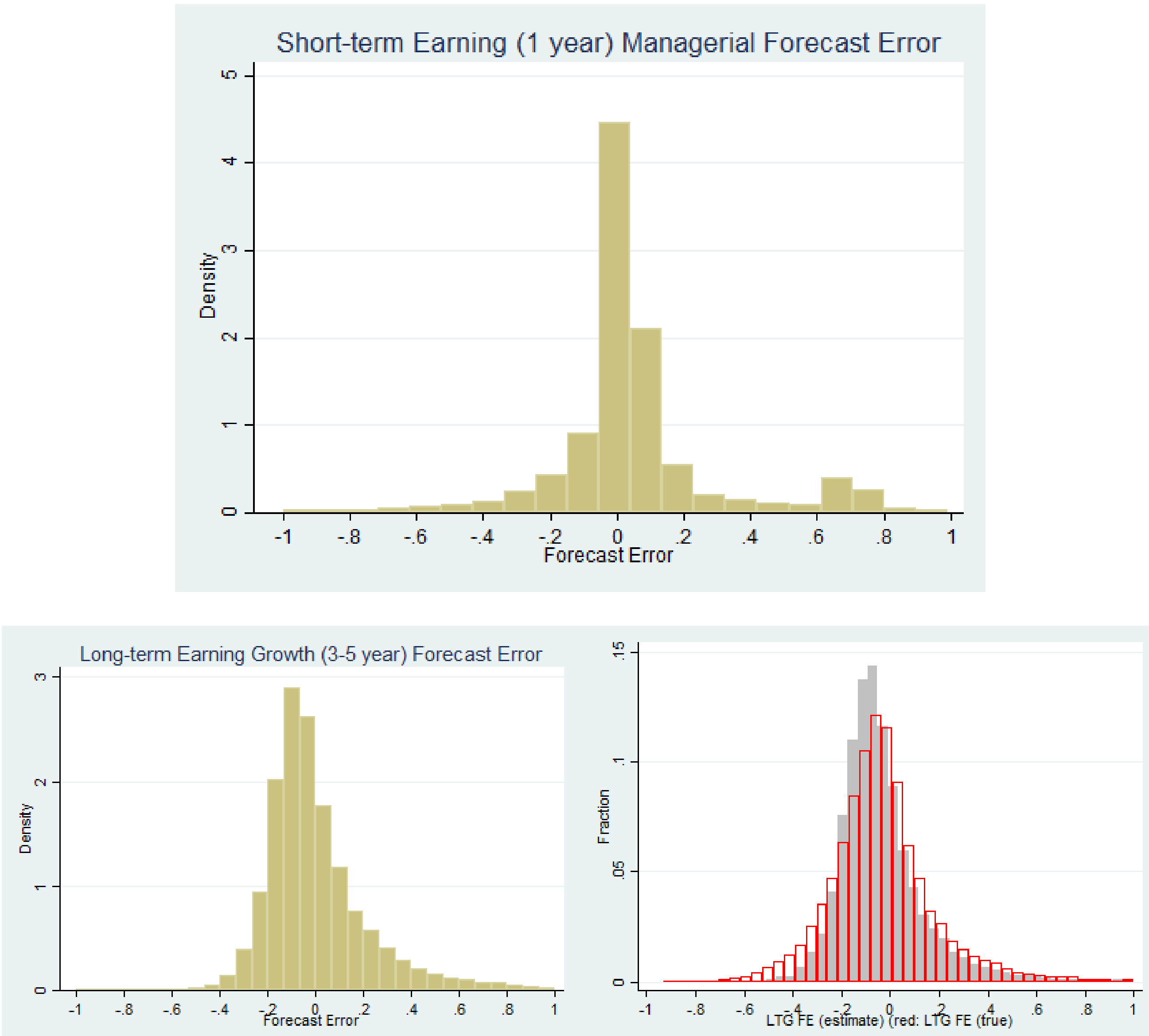


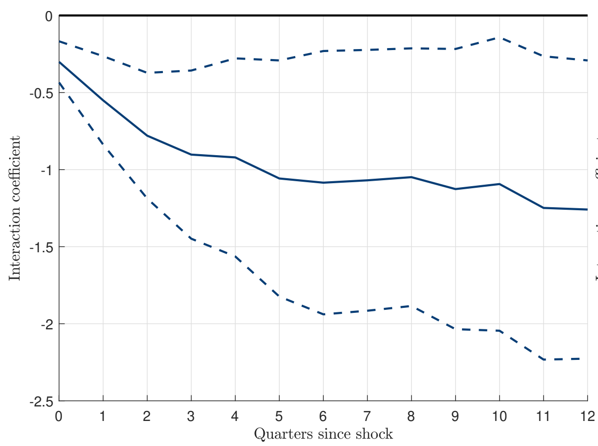
Figure 3: Dynamics of Differential Responses: Analyst's Long-term Growth Forecast Error

This figure plots firms' dynamic differential responses in investment and sales growth to monetary shocks β_h over quarters h. Coefficients are estimated from the following regressions.

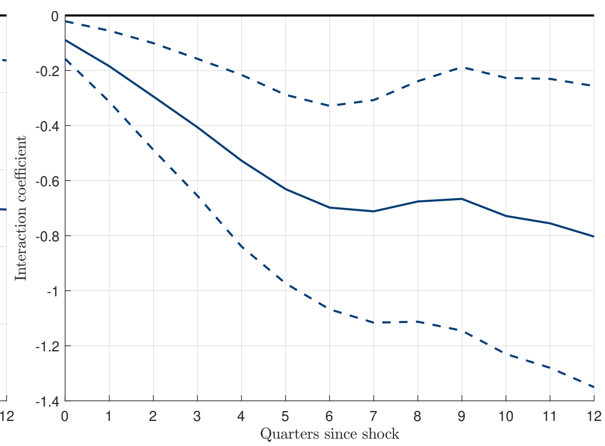
$$\begin{aligned}\Delta \log y_{i,t+h} =& \alpha_i + \alpha_{s,t} + \lambda_h \text{Forecast Error}_{i,t-1} + \beta_h \text{Forecast Error}_{i,t-1} \epsilon_t^m \\ &+ \gamma_h \text{Forecast Error}_{i,t-1} \Delta GDP_{i,t-1} + \Gamma_h' Z_{i,t-1} + \epsilon_{i,t+h}\end{aligned}$$

Dashed lines report 90% error bands.

(a) Physical Capital Investment



(b) Customer Capital Investment



(c) Real Sales Growth

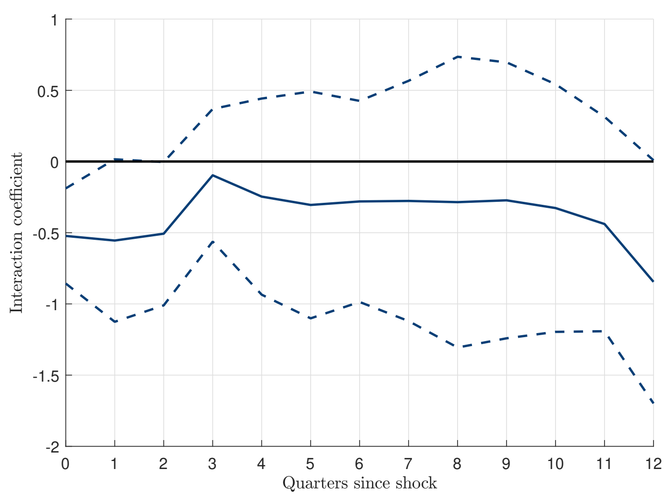


Figure 4: Heterogeneous Investment Sensitivities to Monetary Shocks by Extrapolation Bias

This figure shows the investment response to monetary policy for overpessimistic firms and overoptimistic firms. Marginal benefit and marginal cost curves as a function of capital investment for firms with same current productivity and customer base but different previous productivity news. Blue solid lines plot the curves before a contractionary monetary policy shock, and red dash lines plot the curves after the shock. Overoptimistic firms who receive good news in the last period have higher marginal benefit than overpessimistic firms who receive bad news. Financial friction generates an upward sloping steep marginal cost curve.

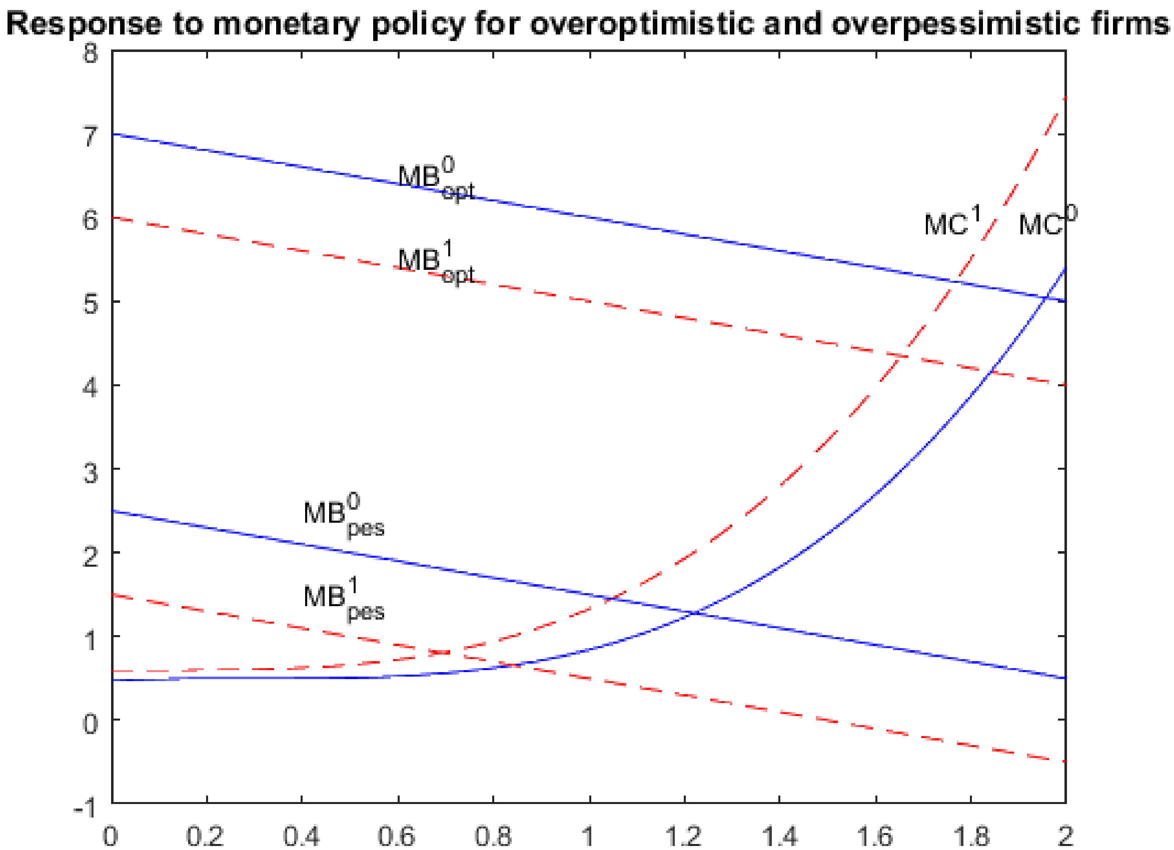


Figure 5: Model Implied Dynamics of Differential Responses

This figure plots firms' dynamic differential responses in investments to monetary shocks β_h over quarters h by forecast error using simulation data from the calibrated model. Coefficients are estimated from the following regressions.

$$\begin{aligned}\Delta \log y_{i,t+h} = & \alpha_i + \alpha_{s,t} + \lambda_h \text{Forecast Error}_{i,t-1} + \beta_h \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ & + \gamma_h \text{Forecast Error}_{i,t-1}\Delta GDP_{i,t-1} + \Gamma_h' Z_{i,t-1} + \epsilon_{i,t+h}\end{aligned}$$

Dashed lines report 90% error bands.

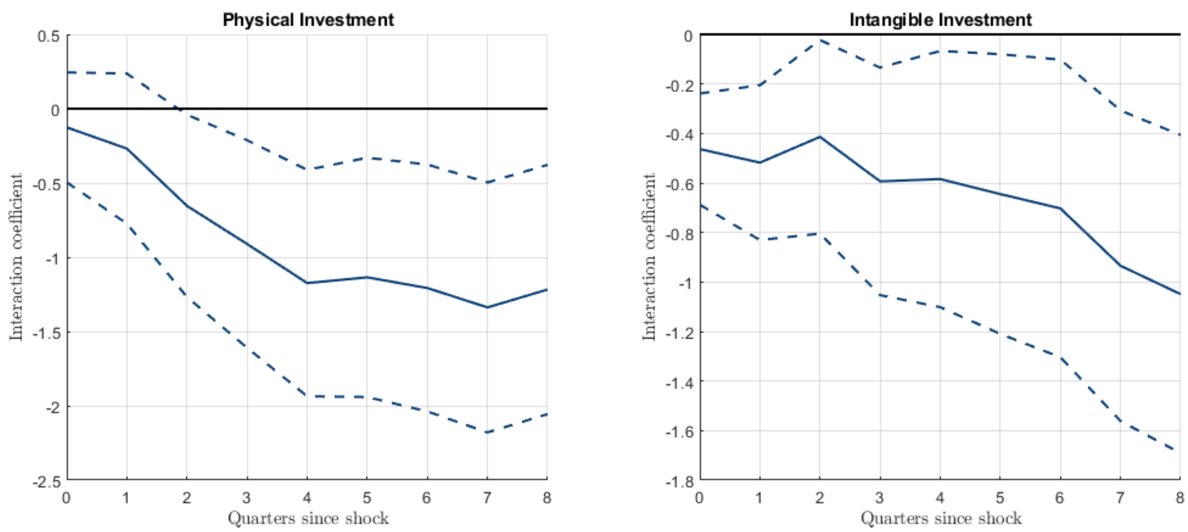


Figure 6: Allocative Efficiency of Monetary Easing

This figure plots percentage deviation of aggregate productivity, output, consumption, physical capital, customer capital and sales people from their steady state value following a 25 basis points monetary easing implied from the model with extrapolative expectation (blue solid line) and rational expectation (red dashed line). As in the data, monetary easing generates an increase in the aggregate productivity when firms form extrapolative expectation. Firm-level overreaction amplifies the aggregate effects of monetary policy.

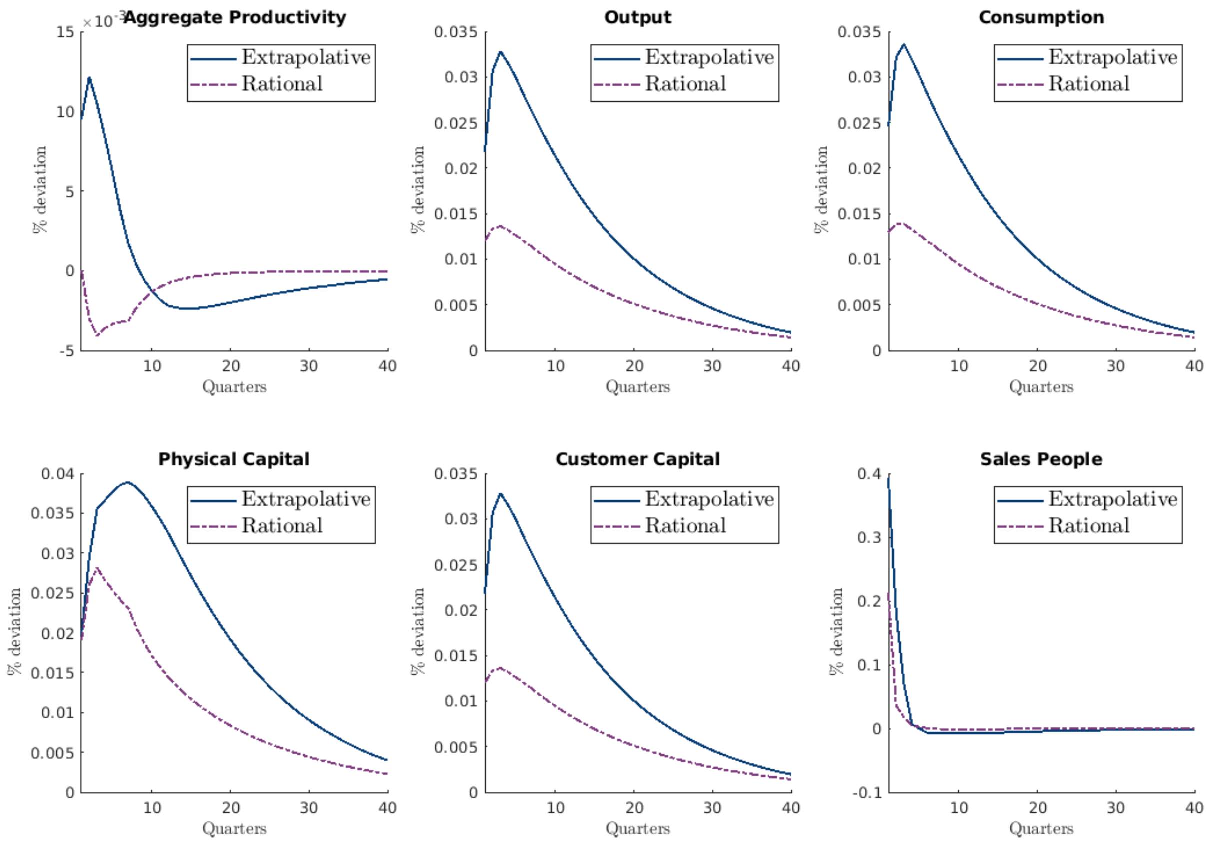


Figure 7: Sensitivity Analysis: η and κ

This figure plots percentage deviation of aggregate productivity, output, consumption, physical capital, customer capital and sales people from their steady state values following a 25 basis points interest rate cut. The first six figures are impulse response functions for different values of η and the last six figures are impulse response functions for different values of κ.

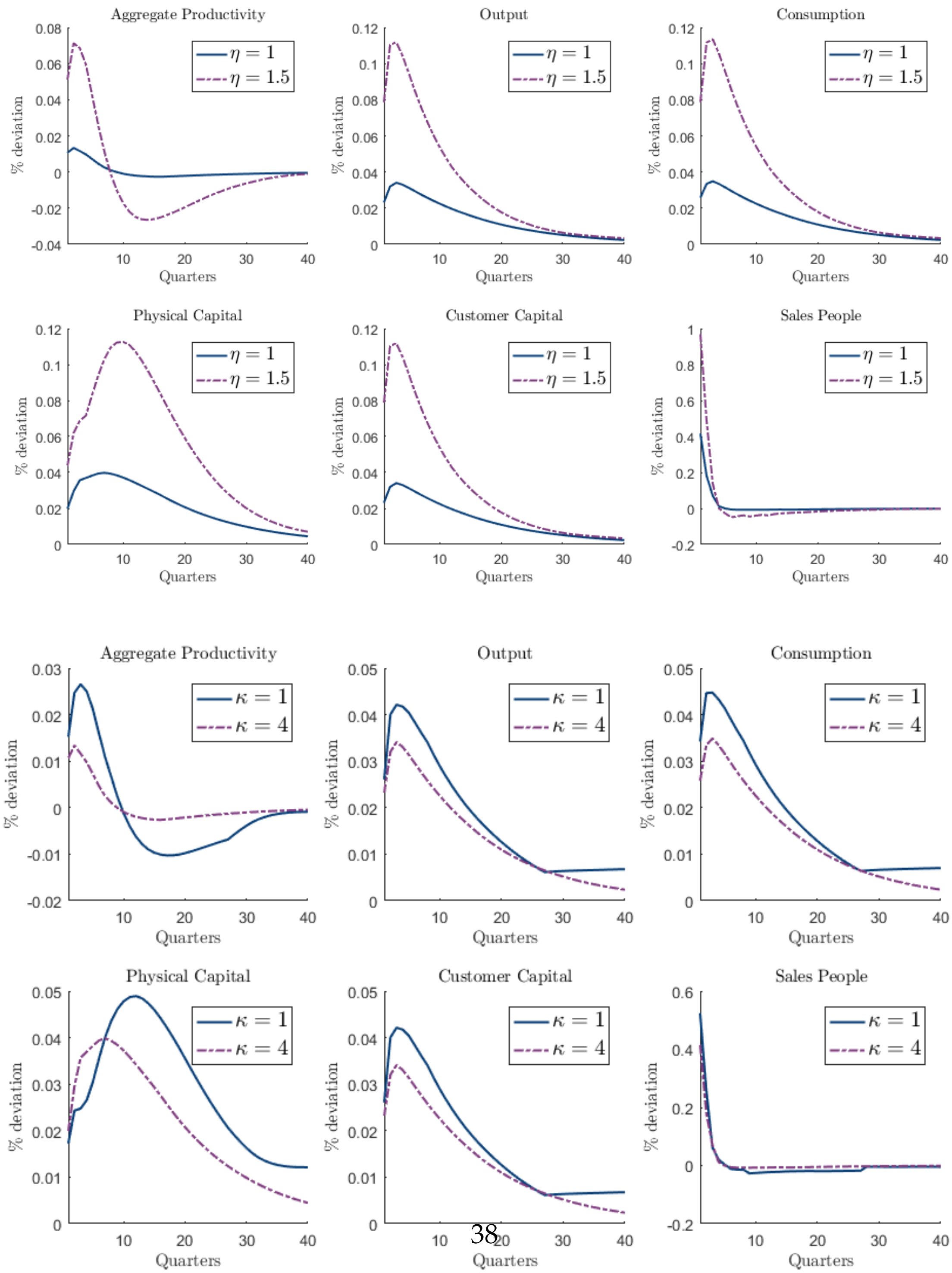
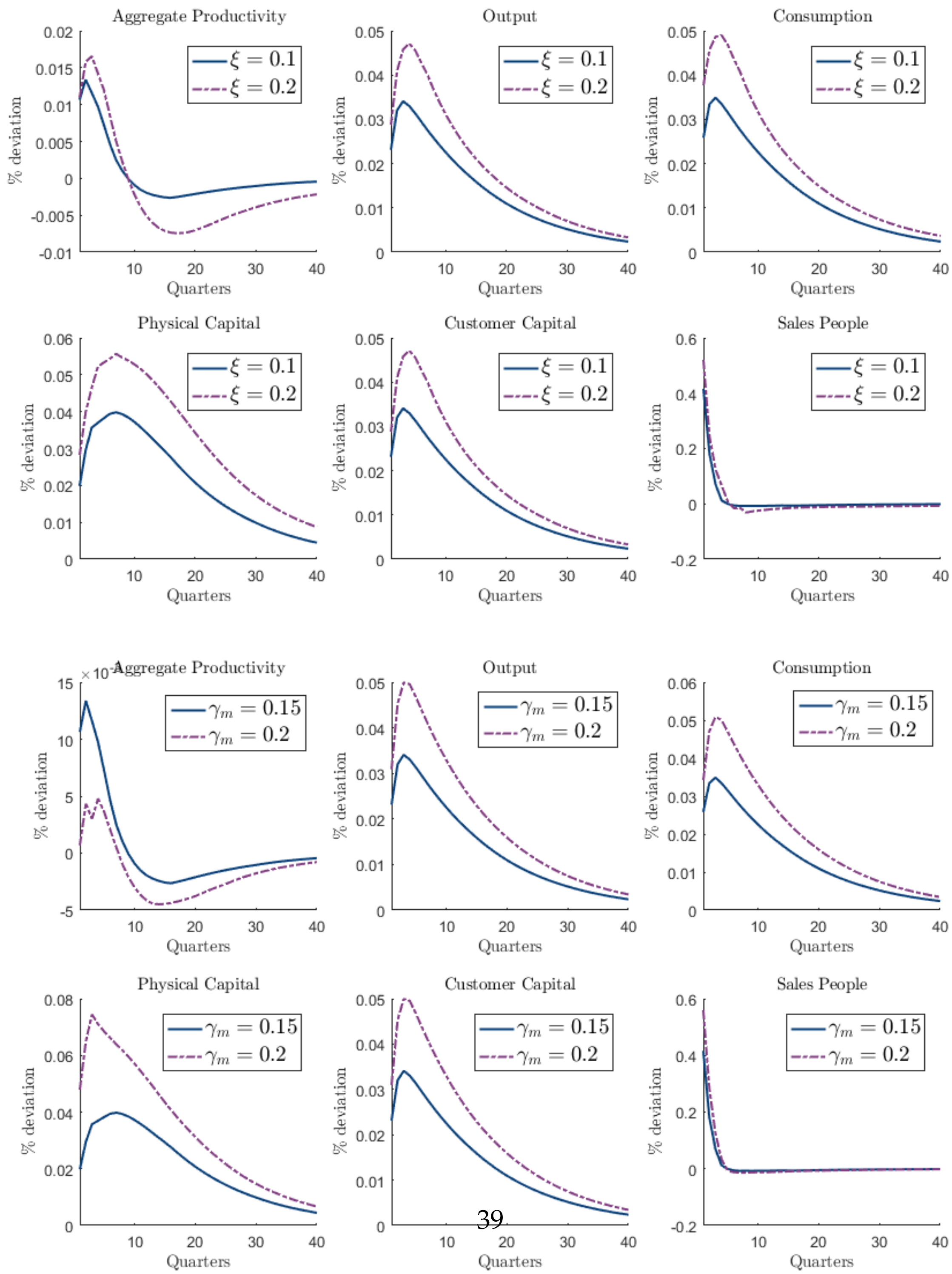


Figure 8: Sensitivity Analysis: ξ and γ_m

This figure plots percentage deviation of aggregate productivity, output, consumption, physical capital, customer capital and sales people from their steady state values following a 25 basis points interest rate cut. The first six figures are impulse response functions for different values of ξ and the last six figures are impulse response functions for different values of γ_m.



Tables

Table 1: Summary Statistics

This table reports the summary statistics of key variables. Panel A presents the summary statistics of monetary policy shocks from 1995Q1 to 2018Q4. Monetary policy shocks are estimated using event study strategy and aggregated using weighted average of daily changes in Fed Funds future prices. Panel B presents the summary statistics of firm-level forecast errors from I/B/E/S. Investment and sales growth are shown in Panel C.

	Panel A: Monetary Policy Shocks			
	FFR (Daily)	Policy News (Daily)	FFR (Quarterly)	Policy News (Quarterly)
Mean	-0.0107	0.000379	-0.0232	0.000231
Median	0	0.00683	-0.00398	0.0105
S.D.	0.0602	0.0403	0.0610	0.0503
Min	-0.413	-0.243	-0.326	-0.292
Max	0.125	0.0986	0.133	0.0873
Observations	200	200	95	95

	Panel B: Forecast Errors	
	Manager's Short-term FE	Analyst's Long-term Growth FE
Mean	0.053	0.005
Median	0.02	-0.042
S.D.	0.265	0.216
Min	-1	-0.996
Max	1	0.999
Observations	34838	44125

	Panel C: Investments and Sales Growth		
	$\Delta \log$ Physical k_{it+1}	$\Delta \log$ Intangible k_{it+1}	$\Delta \log$ Sales$_{it+1}$
Mean	0.017	0.026	0.015
Median	0.017	0.026	0.015
S.D.	0.072	0.035	0.179
1st Percentile	-0.195	-0.055	-0.665
25th Percentile	-0.015	0.006	-0.050
75th Percentile	0.033	0.040	0.088
99th Percentile	0.375	0.173	0.641
Observations	159693	154588	159949

Table 2: Correlation Matrix: Forecast Error and Other Firm Characteristics

This table reports the correlation matrix for the key variables including forecast error, size, age, leverage, liquidity, sales growth and intangibility. Panel A shows the correlation between manager's forecast error and other firm variables. Panel B shows the correlation between analyst's forecast error and other firm variables.

Panel A: Correlation between analyst's forecast error and other variables

	Leverage	Size	Liquidity	Sales Growth	Age	Intangibility	Forecast Error
Leverage	1.00						
Size	0.28	1.00					
Liquidity	-0.42	-0.26	1.00				
Sales Growth	-0.01	-0.01	-0.00	1.00			
Age	0.06	0.50	-0.18	-0.03	1.00		
Intangibility	-0.02	-0.02	0.03	-0.16	-0.01	1.00	
Forecast Error	0.12	-0.25	-0.10	-0.00	-0.08	-0.01	1.00

Panel B: Correlation between manager's forecast error and other variables

	Leverage	Size	Liquidity	Sales Growth	Age	Intangibility	Forecast Error
Leverage	1.00						
Size	0.34	1.00					
Liquidity	-0.41	-0.32	1.00				
Sales Growth	-0.00	-0.01	0.01	1.00			
Age	0.11	0.51	-0.23	-0.03	1.00		
Intangibility	-0.23	-0.25	0.44	-0.11	-0.16	1.00	
Forecast Error	-0.09	0.01	0.09	0.04	-0.02	-0.01	1.00

Table 3: Predictable Forecast Errors

This table reports estimate of the following regressions:

$$\text{Forecast Error}_{i,t} = \alpha_i + \alpha_t + \beta X_{i,t-1} + \epsilon^m_{i,t}$$

where the dependent variable is the next year's firm-level forecast errors, defined as realized minus predicted earnings. $X_{i,t-1}$ is firm-level variables including earning forecast, investment and profit for manager's short-term forecast errors in Panel A. $X_{i,t-1}$ is firm-level forecast revisions in the last three years for analyst's long-term forecast errors in Panel B. The standard deviation of future forecast errors is 0.21, the standard deviation of forecast is 1.06, the standard deviation of current investment is 0.19 and the standard deviation of current profit is 1.62. The firm and year fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Manager's Forecast Errors (2003-2018) Realized - Forecasted Short-term Earnings			
Forecast_{t-1}	-0.022***		
	(0.00)		
Investment_{t-1}		-0.076***	
		(0.02)	
Profit_{t-1}			-0.014***
			(0.00)
Observations	5686	5670	5699
R^2	0.432	0.427	0.431
Firm FE	yes	yes	yes
Year FE	yes	yes	yes
Firm clustering	yes	yes	yes

Panel B: Analyst's Forecast Errors (1995-2018) Model Implied Realized - Forecasted Long-term Earnings Growth			
$(E^c_t - E^c_{t-1})[LTG]$	-0.20***		
	(0.05)		
$(E^c_t - E^c_{t-2})[LTG]$		-0.29***	
		(0.06)	
$(E^c_t - E^c_{t-3})[LTG]$			-0.35***
			(0.08)
Observations	52635	45934	40662
R^2	0.417	0.402	0.402
Firm FE	yes	yes	yes
Year FE	yes	yes	yes
Firm clustering	yes	yes	yes

Table 4: Differential Responses in Investment and Sales Growth by Forecast Error

This table reports firms' differential responses in investment and sales growth to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\Delta \text{log} y_{i,t+1} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m$$
$$+ \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t}$$

where the left hand side is the log difference of *dependent variable* in quarter t. Column (1) to (3) reports the responses in physical capital investment decisions. Column (4) to (6) reports the responses in customer capital investment and column (7) to (9) reports the responses in quarter sales growth. ϵ_t^m is the monetary shock. $Z_{i,t-1}$ is a set of firm control variables including size, market-to-book ratio, liquidity, leverage, a dummy for dividend payout and past sales growth. Firm variables are standardized. Periods of financial crisis (2008Q3 to 2009Q2) are excluded. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Physical Capital Investment			Customer Capital Investment			Real Sales Growth		
	Panel A: Manager's Forecast Error (2003Q1 to 2018Q4)								
$\epsilon_t^m \times FE_{t-1}$	-0.99	-1.19*	-1.27*	-0.63***	-0.71***	-0.58**	-3.54*	-4.45*	-4.12
	(0.74)	(0.61)	(0.69)	(0.17)	(0.23)	(0.26)	(2.08)	(2.40)	(2.47)
ϵ_t^m			-0.93			-0.62			2.38
			(2.22)			(1.94)			(3.05)
FE_{t-1}	0.004***	0.003***	0.003***	0.000	0.001*	0.001**	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	35528	33822	33838	34853	33148	33164	35559	33824	33840
R^2	0.178	0.195	0.175	0.595	0.618	0.572	0.114	0.174	0.158
	Panel B: Analyst's Forecast Error (1995Q1 to 2018Q4)								
$\epsilon_t^m \times FE_{t-1}$	-1.19***	-1.21***	-1.22***	-0.39**	-0.36**	-0.22	-1.52*	-2.09**	-1.80*
	(0.33)	(0.32)	(0.33)	(0.16)	(0.17)	(0.21)	(0.84)	(0.81)	(0.95)
ϵ_t^m			-0.56			-1.09			8.89**
			(1.23)			(0.88)			(3.75)
FE_{t-1}	-0.005***	-0.005***	-0.007***	-0.003***	-0.003***	-0.004***	0.001	-0.001	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	146609	138764	138766	141873	134171	134173	146886	138831	138833
R^2	0.155	0.177	0.156	0.494	0.518	0.468	0.105	0.145	0.126
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 5: Differential Responses in Investment and Sales Growth by Forecast Error (Dummy)

This table reports firms' differential responses in investment and sales growth to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\begin{aligned}\Delta \log y_{i,t} =& \alpha_i + \alpha_{s,t} + \lambda \mathbb{1}_{FE_{t-1}>0} + \beta \mathbb{1}_{FE_{t-1}>0} \epsilon_t^m \\ &+ \gamma \mathbb{1}_{FE_{t-1}>0} \Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t}\end{aligned}$$

where the left hand side is the log difference of *dependent variable* in quarter t. Column (1) to (3) reports the responses in physical capital investment decisions. Column (4) to (6) reports the responses in customer capital investment and column (7) to (9) reports the responses in quarter sales growth. ϵ_t^m is the monetary shock. $Z_{i,t-1}$ is a set of firm control variables including size, market-to-book ratio, liquidity, leverage, a dummy for dividend payout and past sales growth. Firm variables are standardized. Periods of financial crisis (2008Q3 to 2009Q2) are excluded. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Physical Capital Investment			Customer Capital Investment			Real Sales Growth		
	Panel A: Manager's Forecast Error (2003Q1 to 2018Q4)								
$\epsilon_t^m \times \mathbb{1}_{FE_{t-1}>0}$	-1.98	-2.29	-2.12	-0.95**	-0.92**	-1.41**	-6.83	-9.27	-9.01
	(2.21)	(1.62)	(1.75)	(0.47)	(0.43)	(0.65)	(6.56)	(6.28)	(6.37)
ϵ_t^m			0.48			1.39			8.18
			(2.27)			(1.99)			(6.28)
$\mathbb{1}_{FE_{t-1}>0}$	0.01***	0.01***	0.01***	0.00***	0.00***	0.00***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	35396	33709	33725	34729	33043	33059	35427	33711	33727
R^2	0.179	0.197	0.176	0.594	0.617	0.571	0.114	0.175	0.158
	Panel B: Analyst's Forecast Error (1995Q1 to 2018Q4)								
$\epsilon_t^m \times \mathbb{1}_{FE_{t-1}>0}$	-1.19	-1.27	-1.19	-0.78**	-0.77**	-0.39	-4.49**	-5.43***	-4.76**
	(1.07)	(0.96)	(0.91)	(0.33)	(0.33)	(0.38)	(1.88)	(1.77)	(2.01)
ϵ_t^m			-0.16			-1.02			10.83***
			(1.31)			(0.95)			(3.99)
$\mathbb{1}_{FE_{t-1}>0}$	-0.007***	-0.007***	-0.096***	-0.005***	-0.003***	-0.006***	0.001**	-0.003	-0.005*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	146609	138764	138766	141873	134171	134173	146886	138831	138833
R^2	0.154	0.176	0.155	0.492	0.517	0.464	0.105	0.145	0.126
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 6: Differential Responses in Investment and Sales Growth by Advertising Intensity

This table reports firms' differential responses in investment and sales growth to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\Delta \log y_{i,t+1} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t}$$

The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) Physical Capital Investment	(2) Customer Capital Investment	(3) Real Sales Growth
	High Advertising Intensity		
	Panel A: Manager's Forecast Error		
$\epsilon_t^m \times FE_{t-1}$	-1.74**	-0.81*	-6.87***
	(0.72)	(0.41)	(2.42)
Observations	24027	23788	24026
R^2	0.196	0.618	0.185
	Panel B: Analyst's Forecast Error		
$\epsilon_t^m \times FE_{t-1}$	-1.40***	-0.43***	-2.93***
	(0.44)	(0.16)	(0.85)
Observations	90765	89089	90812
R^2	0.177	0.539	0.158
	Low Advertising Intensity		
	Panel A: Manager's Forecast Error		
$\epsilon_t^m \times FE_{t-1}$	0.03	-0.33	1.68
	(1.29)	(0.23)	(4.75)
Observations	9740	9304	9743
R^2	0.222	0.635	0.200
	Panel B: Analyst's Forecast Error		
$\epsilon_t^m \times FE_{t-1}$	-0.74*	-0.21	0.05
	(0.39)	(0.29)	(0.84)
Observations	47477	44561	47497
R^2	0.188	0.495	0.153
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time sector FE	yes	yes	yes
Time clustering	yes	yes	yes

Table 7: Differential Responses in Profit Margin by Forecast Error

This table reports firms' differential responses in profit margin to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\Delta \log y_{i,t} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m$$
$$+ \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t}$$

where the left hand side is the log difference of profit margin in quarter t. Column (1) to (3) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{COGS}}$. Column (4) to (6) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{(COGS+XSGA)}}$ and column (7) to (9) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{(COGS+(XSGA-XRD-RDIP))}}$. ϵ_t^m is the monetary shock. $Z_{i,t-1}$ is a set of firm control variables including size, market-to-book ratio, liquidity, leverage, a dummy for dividend payout and past sales growth. Firm variables are standardized. Periods of financial crisis (2008Q3 to 2009Q2) are excluded. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level, except that profit margin is winsorized at the 5% level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$\frac{\text{SALES}}{\text{COGS}}$			$\frac{\text{SALES}}{\text{(COGS+XSGA)}}$			$\frac{\text{SALES}}{\text{(COGS+(XSGA-XRD-RDIP))}}$	
				Panel A: Manager's Forecast Error					
$\epsilon_t^m \times FE_{t-1}$	-1.13**	-1.94***	-1.62**	-0.39	-1.55**	-1.35*	-0.53	-1.48	-1.23
	(0.57)	(0.62)	(0.64)	(0.65)	(0.69)	(0.70)	(1.01)	(1.04)	(1.04)
ϵ_t^m			3.43			3.19			3.28
			(2.29)			(3.01)			(3.09)
FE_{t-1}	0.000	-0.000	-0.000	-0.001*	-0.001**	-0.001***	-0.001	-0.001	-0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	32454	30900	30914	33282	31651	31667	30642	29155	29202
R^2	0.080	0.086	0.060	0.085	0.115	0.096	0.087	0.115	0.098
				Panel B: Analyst's Forecast Error					
$\epsilon_t^m \times FE_{t-1}$	-0.71***	-0.74***	-0.79***	-0.71**	-0.88**	-0.87**	-0.51	-0.64*	-0.65*
	(0.25)	(0.23)	(0.23)	(0.33)	(0.36)	(0.39)	(0.31)	(0.33)	(0.36)
ϵ_t^m			0.34			-0.75			-0.62
			(0.65)			(1.64)			(1.30)
FE_{t-1}	0.002***	0.001***	0.001***	0.002***	0.001**	0.001*	0.002***	0.001*	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	134341	127256	127260	136294	129018	129020	123271	117267	117279
R^2	0.056	0.061	0.043	0.071	0.091	0.069	0.070	0.091	0.071
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 8: Differential Responses in Profit Margin by Forecast Error (dummy)

This table reports firms' differential responses in profit margin to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\begin{aligned}\Delta \log y_{i,t} =& \alpha_i + \alpha_{s,t} + \lambda \mathbb{1}_{\text{Forecast Error}_{i,t-1}>0} + \beta \mathbb{1}_{\text{Forecast Error}_{i,t-1}>0}\epsilon_t^m \\ &+ \gamma \mathbb{1}_{\text{Forecast Error}_{i,t-1}>0}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t}\end{aligned}$$

where the left hand side is the log difference of profit margin in quarter t. Column (1) to (3) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{COGS}}$. Column (4) to (6) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{(COGS+XSGA)}}$ and column (7) to (9) reports the responses in profit margin defined as $\frac{\text{SALES}}{\text{(COGS+(XSGA-XRD-RDIP))}}$. ϵ_t^m is the monetary shock. $Z_{i,t-1}$ is a set of firm control variables including size, market-to-book ratio, liquidity, leverage, a dummy for dividend payout and past sales growth. Firm variables are standardized. Periods of financial crisis (2008Q3 to 2009Q2) are excluded. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level, except that profit margin is winsorized at the 5% level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$\frac{\text{SALES}}{\text{COGS}}$			$\frac{\text{SALES}}{\text{(COGS+XSGA)}}$			$\frac{\text{SALES}}{\text{(COGS+(XSGA-XRD-RDIP))}}$	
				Panel A: Manager's Forecast Error					
$\epsilon_t^m \times \mathbb{1}_{FE_{t-1}>0}$	-1.29	-2.84*	-2.91	0.98	-0.67	-0.89	-1.14	-2.74	-2.42
	(1.60)	(1.66)	(1.85)	(1.51)	(1.71)	(1.79)	(1.97)	(2.19)	(2.31)
ϵ_t^m			5.15*			3.67			4.76
			(2.70)			(3.31)			(3.14)
$\mathbb{1}_{FE_{t-1}>0}$	-0.000	-0.001	-0.001	-0.002**	-0.002	-0.002**	-0.002*	-0.001	-0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	32370	30825	30839	33198	31576	31592	30566	29088	29135
R^2	0.080	0.086	0.060	0.086	0.115	0.096	0.087	0.115	0.098
				Panel B: Analyst's Forecast Error					
$\epsilon_t^m \times \mathbb{1}_{FE_{t-1}>0}$	-0.82*	-0.83*	-0.90*	-1.92***	-2.04***	-2.05**	-1.41**	-1.46**	-1.50**
	(0.44)	(0.47)	(0.49)	(0.61)	(0.72)	(0.82)	(0.65)	(0.67)	(0.75)
ϵ_t^m			0.70			0.08			-0.02
			(0.64)			(1.63)			(1.21)
$\mathbb{1}_{FE_{t-1}>0}$	0.003***	0.002***	0.002**	0.003***	0.001	0.001	0.002**	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	134341	127256	127260	136294	129018	129020	123271	117267	117279
R^2	0.056	0.061	0.043	0.071	0.091	0.069	0.070	0.091	0.071
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 9: Parameters for Baseline Model (Quarterly)

This tables summarizes the external fixed and internal calibrated parameters used to solve and simulate the model. All values are quarterly.

Description	Parameter	Value	Target Moment/Source
Panel A: Household			
Discount factor	β	0.99	Annual interest rate (4%)
Labor disutility	Ψ	1.4	Steady state employment (1)
Panel B: Firm Producer			
Technology			
Capital coefficient	α	0.63	Standard
Span of control (matching)	η	1	CRS matching technology
Matching function elasticity	γ_m	0.15	Buyers'time/Sellers' time
Matching function coefficient	ξ	0.1	Internal calibrated
Investment and Financing			
Equity variable issuance cost	λ	0.02	Internal calibrated
Physical capital depreciation	δ	0.03	12% annual depreciation rate
Customer capital depreciation	δ_n	0.05	20% annual depreciation rate
Sales people adjustment cost	κ	4	Internal calibrated
Productivity			
Productivity persistency	ρ_z	0.87	Internal calibrated
Productivity volatility	σ_z	0.1	Internal calibrated
Extrapolation	ν	1.3	Internal calibrated
Panel C: New Keynesian Block			
Demand elasticity	γ	10	Steady state markup (11%); labor share (58%)
Taylor rule coefficient	φ_π	1.25	Ottonello & Winberry (2020)
Price adjustment cost	φ	90	Phillips Curve slope (0.1)
Persistence of monetary shock	ρ_m	0.5	Ottonello & Winberry (2020)

Table 10: Internal Calibrated Parameters and Model Fit

This table reports moments generated by the model. I simulate 50 economies for 100 quarters. Each sample consists of 5,000 firms. This table shows cross-simulation averages. The data are from the quarterly CRSP-Compustat file covering periods from 1995Q1 to 2018Q4.

Description	Parameter	Value	Target Moment	Data	Model
Labor disutility	Ψ	0.18	Aggregate Labor Supply	1	1
Labor adjustment cost	κ	4	$\frac{\text{XSGA-XRD-RDIP}}{\text{SALES}}$	0.214	0.184
Productivity persistency	ρ_z	0.87	Auto Corr Profitability	0.834	0.912
Productivity volatility	σ_z	0.1	Stdev Profitability	0.065	0.078
Extrapolation	θ	1.3	Corr Forecast Error and Profitability	-0.054	-0.067
Equity variable issuance cost	λ	0.03	Equity/Asset	0.01	0.011

Table 11: Empirical Results, Model and Data

This table compares the baseline empirical estimates of heterogeneous investment sensitivities using both real data and simulated data from the calibrated model.

	Physical Capital Investment		Customer Capital Investment		Sales Growth	
	Data	Model	Data	Model	Data	Model
$\epsilon_t^m \times FE_{t-1}$	-1.21	-3.99	-0.56	-0.36	-2.09	-1.11
	(0.56)		(0.13)		(2.40)	
Firm FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
R^2	0.177	0.966	0.518	0.410	0.145	0.848

Table 12: Sensitivity Analysis: Model Moments

This table shows the target moments computed from model with different parameter values.

Moments	$\frac{\text{XSGA-XRD-RDIP}}{\text{SALES}}$	Corr(Profit,FE)	$\frac{\text{Equity}}{\text{Total Asset}}$	std(Profit)	Autocorr(Profit)
Baseline calibration	0.184	-0.067	0.011	0.078	0.913
$\eta = 1.5$	0.374	-0.365	0.117	0.060	0.862
$\gamma_m = 0.2$	0.178	-0.148	0.014	0.076	0.906
$\kappa = 1$	0.135	-0.011	0.108	0.106	0.906
$\xi = 0.2$	0.125	0.000	0.129	0.111	0.904

Online Appendix

A Details on Data Construction

A.1 Variables Construction

A.1.1 Monetary Shocks

I use the daily measures of monetary policy shocks from Gurkaynak, Sack and Swanson (2005) and Gorodnichenko and Weber (2016) (”GSS” and ”GW”) as the baseline measures in the main analysis and the measures from Nakamura and Steinsson (2018), as well as Gertler and Karadi (2015) in the robustness test.

”GSS” and ”GW” measure monetary shocks as the changes in the current month’s federal funds futures rate in a 30 minutes’ narrow window around FOMC announcement. I excludes unscheduled meetings and conference calls, which helps to mitigate the problem that monetary surprises may contain private central bank information about the state of the economy (Meier and Reinelt, 2020). I further excludes the apex of the financial crisis from 2008Q3 to 2009Q2. The sample runs from 1995-2018. I also use the policy news shock of Nakamura and Steinsson (2018) in the robustness check.

I follow Ottonello and Winberry (2020) to aggregate the shocks to quarterly frequency. I assign daily shocks fully to the current quarter if they occur on the first day of the quarter. If they occur within the quarter, I partially assign the shock to the subsequent quarter. This procedure weights shocks across quarters corresponding to the amount of time agents have to respond.

Results based on Nakamura and Steinsson (2018)’s policy news shock can be found in Figure **??** in Appendix D.

A.1.2 Aggregate Variables

The aggregate variables in the main regression test include price deflator (IPD: Nonfarm business sector: implicit price deflator), four lags of GDP growth (GDPC1: Real Gross Domestic Product), the inflation rate (CPIAUCSL: Consumer Price Index for All Urban Consumers: All Items), the unemployment rate (UNRATE: Unemployment Rate) available from Federal Reserve Bank of St. Louis as well as their Greenbook forecasts and forecast revisions available from Federal Reserve Bank of Philadelphia.

A.1.3 Industry-level Variables

I define the weighted average (by sales) of firm-level advertising expenditure: $\frac{\text{XAD}}{\text{SALES}}$ within the same industry. Notice that Compustat variable XAD is only available at the annual frequency, the measure of industry-level advertising intensity is computed at the 2-digit SIC industry-year level. However, XAD has lots of missing values. I follow the imputation method in Belo, Gala, Salomao and Vitorino (2021) to recover the missing values. I calculate the customer capital stocks using data starting in 1972 when companies start to report advertising expenses in the "Supplementary Income Statement Information" schedule. We impute missing advertising data based on the observed Selling, General and Administrative (SG&A) expenses using the firm-level average ratio of advertising expenses-to-SG&A ratio for the years in which neither of these values is missing. Given the different disclosure requirements throughout the years, however, I cap the imputed amount at 1% of sales for the years from 1972 through 1993 (to make the imputed values consistent with the reporting standards). I exclude from the sample all the firms with missing XAD during the entire sample period.[19]

A.1.4 Earning Forecasts and I/B/E/S Data Set

Analyst's long-term earning growth forecast

Analyst's subjective long-term earning growth forecast is defined as the "expected annual increase in operating earnings over the company's next full business cycle", a period ranging from three to five years. Analyst's median (MEDEST) consensus forecasts of firms' long-term earnings growth (MEASURE == "EPS", FPI==0) is available in Adjusted Summary History database. I require non-missing IBES permanent ticker (TICKER !=.) and only keep US firms (USFIRM == 1) reporting in US dollars (curcode = USD). I average monthly observations within a year to represent annual consensus forecast in order to use the most of available observations for each firm within each year.

While Compustat mainly records Generally Accepted Accounting Principles (GAAP) earnings, managers and analysts often use so-called "street earnings", which adjust for certain nonrecurring items (Bradshaw and Sloan 2002). These are the numbers that analyst forecasts aim to match. I obtain the realized earning ("street earning") from IBES Unadjusted Detail

[19] In 1994, the SEC passed Financial Reporting Release 44 (FRR 44), which eliminated the disclosure requirement of advertising expenditures in public firms' annual reports. Before the passage of FAR 44 (which became effective on December 20, 1994), public firms were required to report advertising spending if it exceeded 1 percent of their total sales (according to the SEC Release AS-125, which became effective for financial statements for periods ending on or after Dec 31, 1972).

Actuals file (also EPS). Realized earnings are computed by realized earnings per share (FY0A) times shares outstanding (SHOUT). The missing value is replaced by Compustat item IB (IB: Income Before Extraordinary Items, has a high correlation with street earning) (Gulen, Ion and Rossi, 2021)

To avoid the timing issue in the regression test, I use model implied long-term realized earning instead of realized earning directly to compute the forecast error. I borrow insights from the accounting literature and use a cross-sectional earnings model to forecast earnings of individual firms, following Hou, Van Dijk, and Zhang (2012), who have adopted an extension and variation of the cross-sectional profitability models in Fama and French (2000, 2006). Specifically, for each year between 1983 and 2018, I estimate the following pooled cross-sectional regressions using a 10-year rolling windows:

$$E_{i,t+h} = \beta_0 + \beta_1 E_{i,t} + \beta_2 A_{i,t} + \beta_3 D_{i,t} + \beta_4 DD_{i,t} + \beta_5 NE_{i,t} + \epsilon_{i,t+h} \tag{31}$$

where $E_{i,t+h}$ denotes the earnings of firm i in year $t+h$ ($h = 3, 4, 5$). $A_{i,t}$ is the total assets, $D_{i,t}$ is the dividend payment, $DD_{i,t}$ is a dummy variable that takes value 1 for dividend payers and 0 otherwise, and $NE_{i,t}$ is a dummy variable that takes value 1 for negative earnings and 0 otherwise. I estimate the above reduced form model using a 10-year rolling windows with $t \in [t-h-10, t-h-1]$ to make sure that I use information up to time t when estimating the model coefficients. For each firm i in year t, I compute the model implied realized earnings $\hat{E}_{i,t+h}$ for year 3 to 5 by multiplying the independent variables as of year t with the coefficients from the pooled regression estimated using the previous ten years of data. I finally calculate the model implied long-term realized earning growth of year t as

$$LTG_t = \frac{1}{3}\left[(\hat{E}_{i,t+3}/E_{i,t})^{1/3} + (\hat{E}_{i,t+4}/E_{i,t})^{1/4} + (\hat{E}_{i,t+5}/E_{i,t})^{1/5}\right] - 1 \tag{32}$$

The forecast error of long-term earning growth is defined as

$$\text{Forecast Error}_{i,t} = LTG_{i,t} - \mathbb{E}^{\nu}(LTG_{i,t}) \tag{33}$$

where $\mathbb{E}^{\nu}(LTG_{i,t})$ is the forecasts of long-term earning growth reported in IBES. The forecast errors that are above 100% or below -100% are dropped. Forecast errors of negative earnings are dropped. All above variables are winsorized at the 1 and 99 percentiles.

Manager's earning forecast

For robustness, I also use manager guidance data to construct forecast error. I use managers' forecasts on the coming fiscal year end earnings per share from IBES Guidance dataset.

US firms with non-missing IBES permanent ticker and US dollars guidance are considered. The sample is from 2003 to 2018. If the guidance is a range, average is taken. Observations are dropped if their earnings estimate end month and announcement month are different. If there are more than one announcement within a year, then the last available announcement in that year is taken.

The forecast error is defined as the scaled difference between the realized earning and its forecast value. The forecast errors that are above 100% or below -100% are dropped. Forecast errors of negative earnings are dropped. All above variables are winsorized at the 1 and 99 percentiles.

$$\text{Forecast Error}_{i,t} = \frac{2(\text{Earning}_{i,t} - \mathbb{E}^{\nu}_{t-1}\text{Earning}_{i,t})}{|\text{Earning}_{i,t}| + |\mathbb{E}^{\nu}_{t-1}\text{Earning}_{i,t}|} \tag{34}$$

IBES-Compustat linkage

To link Compustat and IBES, I complete two steps. First, Compustat provides a linking header table between GVKEY and IBES ticker ibtic in security table. Second, I link the missing ones after first step via iclink macro which links CRSP and IBES, and finally I merge IBES and Compustat.

A.1.5 Firm-level Variables from Compustat

I draw firm-level variables from quarterly Compustat, a panel of publicly listed U.S. firms. The main measure are firm's investment and markup.

Investment

I use perpetual inventory method to compute physical capital stock and intangible capital stock.

$$k_{t+1} = (1-\delta)k_t + i_t \tag{35}$$

Physical Investment

Investment is defined as $\Delta log(k_{i,t+1})$, the log-differences in real capital stock of firm i at the end of period t. I set the initial value to be the level of gross plant, property, and equipment (PPEGTQ) in the first period in which this variable is reported in Compustat. The annualized depreciation rate δ is 0.1 for physical investment. From this period onwards, I compute the evolution of physical capital using the changes of net plant, property, and equipment ($\text{PPENTQ}_{i,t+1} - \text{PPENTQ}_{i,t}$), which is a measure of net investment $i_{i,t} - \delta k_{i,t}$ with significantly more observations than PPENTQ (net of depreciation). 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 nearest two values of PPENTQ; if two or more consecutive observations are missing we do not do any imputation. I further deflate the nominal capital stock using BLS implicit price deflator. Investment is winsorized at 1 and 99 percentiles.

Intangible Investment

where the annualized value δ is 0.1 for physical investment and 0.2 (Falato, Kadyrzhanova, and Sim (2013)) for intangible investment. The initial value is the first available PPENTQ for tangible investment and $\frac{XGAQ_0}{g+\delta} = \frac{XGAQ_0}{0.3}$ for intangible investment. Net investment $i_{i,t} - \delta k_{i,t}$ is $\text{PPENTQ}_{i,t+1} - \text{PPENTQ}_{i,t}$ for physical investment.

I follow Peter and Taylor (2017) to measure the stock of intangible capital by accumulating a fraction of past $SG\&A$ spending using the perpetual inventory method. I measure $SG\&A$ as Compustat variable XSGAQ (raw measure) or XSGAQ-XRDQ-RDIPQ (baseline measure) to further isolate (non-$R\&D$) $SG\&A$. I set missing XSGAQ, XRDQ, RDIPQ to zero and negative XSGAQ, XRDQ, RDIPQ to missing. When XRDQ exceeds XSGAQ but is less than COGSQ, I measure $SG\&A$ as XSGAQ in the baseline measure. I interpolate $SG\&A$ using their nearest non-missing values when firm's assets are also missing. The annualized depreciation rate δ is 0.2 for intangible investment in the baseline analysis (Falato, Kadyrzhanova, and Sim (2013)). The initial value is the first available $SG\&A$ adjusted by its growth rate and depreciation rate ($\frac{XGAQ_0}{g+\delta} = \frac{XGAQ_0}{0.3}$). I follow Hulten and Hao (2008), Eisfeldt and Papanikoloau (2014) and Zhang (2014) in counting only 30% of $SG\&A$ spending as an investment in intangible capital. I further deflate the nominal capital stock using BLS implicit price deflator. Robustness check with different values of depreciation rates is included. Investment is winsorized at 1 and 99 percentiles.

Profit Margin

I follow Crouzet and Eberly (2018), De Loecker and Eeckhout (2017), Gutierrez and Philippon (2018) to measure firm-level proxy for "Markup" (profit margin) (Firm-level approach and Hall (2018) for Industry-level approach). As discussed by De Loecker and Eeckhout (2017), within a particular industry, the ratio of revenue to cost of goods sold is a correct measure of firm-level markups, up to an industry-specific constant. Note that while this affects the levels of markups, it does not change the trends, which are only driven by changes in the ratio of sales to cost of goods sold at the firm-level.

I adopt three measures of markup below, where μ is the output elasticity:

1.

$$\text{Markup} = \frac{\text{SALEQ}}{\text{COGSQ}}$$

2.

$$\text{Markup} = \frac{\text{SALEQ}}{\text{COGSQ+XSGAQ}}$$

3.

$$\text{Markup} = \frac{\text{SALEQ}}{\text{COGSQ + (XSGAQ-XRDQ-RDIPQ)}}$$

To avoid the trend effect of markup, I demean the firm-level markups at the 3-digit NAICS and year level before I compute the log-differences. As a result, the changes in markups are not affected by the estimate of industry-specific elasticity. Markup is winsorized at 5 and 95 percentiles by year to avoid extreme outliers.

Other Variables

1. Leverage: defined as the ratio of total debt (DLCQ + DLTTQ) to total assets (ATQ)
2. Real sales growth: measured as log-differences in sales (SALEQ) deflated using BLS implicit price deflator.
3. Size: measured as the log of total real assets, deflated using BLS implicit price deflator.
4. Liquidity: measured as the ratio of cash and short-term investments (CHEQ) to total assets.
5. Current asset ratio: measured as the ratio of current asset (ACTQ) to total assets.
6. Dividend payer: defined as a dummy variable taking a value of one in firm-quarter observations in which the firm paid dividends to preferred stock of the company (DVPQ)
7. Sectoral dummies
   (a) Agriculture, forestry, and fishing: SIC < 999;
   (b) Mining: SIC $\in [1000, 1499]$;
   (c) Construction: SIC $\in [1500, 1799]$;
   (d) Manufacturing: SIC $\in [2000, 3999]$;
   (e) Transportation, communications, electric, gas, and sanitary services: SIC $\in [4000, 4999]$;
   (f) Wholesale trade: SIC $\in [5000, 5199]$;

(g) Retail trade SIC $\in$ [5200, 5999];

(h) Services: SIC $\in$ [7000, 8999].

A.2 Sample Selection

I apply the following filters to my sample:

1. Firms in finance, insurance, and real estate sectors (SIC $\in$ [6000, 6799]), utilities (SIC $\in$ [4900, 4999]), nonoperating establishments (SIC = 9995), and industrial conglomerates (SIC = 9997).
2. Firms not incorporated in the United States.
3. Firms with negative or missing sales or assets.
4. Investment spell is shorter than 12 quarters.
5. Negative liquidity
6. Small firms with gross capital (PPEGTQ) less than 5M.

Table A.1: High Advertising Intensity Industry

SIC-2	Industry
1	Agricultural production crops
7	Agricultural services
20	Food and kindred products
21	Tobacco products
23	Apparel and other finished products from fabrics
25	Furniture and fixtures
27	Printing, publishing, and allied industries
28	Chemicals and allied products
30	Rubber and miscellaneous plastics products
31	Leather and leather products
34	Fabricated metal products, except machinery and transportation equipment
36	Electronic and other electrical equipment and components, except computer equipment
37	Transportation equipment
38	Measuring, analyzing, and controlling instruments
39	Miscellaneous manufacturing industries
47	Transportation services
48	Communications
52	Building materials, hardware, garden supply, and mobile home dealers
53	General merchandise stores
56	Apparel and accessory stores
57	Home furniture, furnishings, and equipment stores
58	Eating and drinking places
59	Miscellaneous retail
72	Personal services
73	Business services
75	Automotive repair, services, and parking
78	Motion pictures
79	Amusement and recreation services
81	Legal services
82	Educational services
86	Membership organizations
89	Miscellaneous services

Table A.2: Low Advertising Intensity Industry

SIC-2	Industry
2	Agriculture production livestock and animal specialties
8	Forestry
10	Metal mining
12	Coal mining
13	Oil and gas extraction
14	Mining and quarrying of nonmetallic minerals
15	Building construction: general contractors and operative builders
16	Heavy construction: other than building construction contractors
17	Construction: special trade contractors
22	Textile mill products
24	Lumber and wood products, except furniture
26	Paper and allied products
29	Petroleum refining and related
32	Stone, clay, glass, and concrete products
33	Primary metal industries
35	Industrial and commercial machinery and computer equipment
40	Railroad transportation
41	Local and suburban transit and interurban highway passenger transportation
42	Motor freight transportation and warehousing
44	Water transportation
45	Transportation by air
50	Wholesale trade: durable goods
51	Wholesale trade: non-durable goods
54	Food stores
55	Automotive dealers and gasoline service stations
70	Hotels, rooming houses, camps, and other lodging
76	Miscellaneous repair services
80	Health services
83	Social services
84	Museums, art galleries, and gardens
87	Engineering, accounting, research, management, and related services
99	Non-classifiable establishments

B Details on the Model

B.1 Representative Household

There is a unit measure continuum of identical households with preferences over consumption C_t and total labor supply: buyers L_t^b and producers L_t^m, whose expected utility is as follows:

$$\sum_{t=0}^{\infty} \beta^t (logC_t - \Psi(L_t^b + L_t^m))$$

subject to the budget constraint:

$$P_tC_t + \frac{B_{t+1}^{rf}}{R_t^{nom}} \leq W_t(L_t^b + L_t^m) + B_t^{rf} + T_t$$

where β is the discount factor of households, Ψ is the disutility of working, P_t is the price index, R_t^{nom} is the nominal rate, W_t is the nominal wage rate, B_t^{rf} is the one-period risk free debt and T_t is the transfer from all firms including the nominal profits.

Every period, the households make decision on the allocation of one unit of time among leisure, working as producer or searching as a buyer in the product market, which determine the real wage in the following optimal condition:

$$w_t = \frac{W_t}{P_t} = -\frac{U_l(C_t, L_t^b + L_t^m)}{U_c(C_t, L_t^b + L_t^m)} = \Psi C_t$$

The decision over consumption and saving in risk-free bonds determine the discount factor, which is linked to nominal rate and inflation rate through the Euler equation:

$$\Lambda_{t+1} = \beta \frac{U_c(C_{t+1}, L_{t+1}^b + L_{t+1}^m)}{U_c(C_t, L_t^b + L_t^m)} = \beta \frac{C_t}{C_{t+1}} = \frac{1}{R_t^{nom}/\Pi_{t+1}}$$

B.2 New Keynesian Block

The New Keynesian block of the model consists of a final good producer who produces final goods, retailers who have quadratic adjustment cost when setting prices (price rigidity) and a monetary authority who sets the interest rate rule. It generates: 1) a New Keynesian Phillips curve relating nominal variables to the real economy and 2) a Taylor Rule which links the monetary policy shock and inflation to the nominal interest rate.

B.2.1 Final Good Producer

There is a representative final good producer who produces the final good Y_t using intermediate goods from all retailers with the production function:

$$Y_t = \left(\int \tilde{y}_{i,t}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}$$

where γ is the elasticity of substitution between intermediate goods. The final good producer solves the following profit maximization problem subject to equation above:

$$\texttt{Max}_{\tilde{y}_{i,t}} \;\; P_t Y_t - \int_0^1 \tilde{p}_{i,t} \tilde{y}_{i,t} di$$

The optimal decision gives the demand curve $\tilde{y}_{i,t} = \left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma} Y_t$ where the price index is $P_t = \left(\tilde{p}_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}$. The final good serves as the numeraire in the model.

B.2.2 Intermediate Retailers

For each production firm j, there is a corresponding retailer i who produces a differentiated variety $Y_{i,t}$ using good $\tilde{y}_{i,t}$ from production firm i as its only input:

$$\tilde{y}_{i,t} = y_{i,t}$$

where the retailers are monopolistic competitors who set their prices $\tilde{p}_{i,t}$ subject to the demand curve generated by the final good producer and the wholesale price of the input P_t. Retailers pay a quadratic menu cost in term of final good $\frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$, to adjust their prices as in Rotemberg (1982), where Y_t is the final good.

The resulting price stickiness comes from the price-setting decisions made by retailers maximizing profits. I follow Rotemberg (1982) except the marginal cost is now the wholesale price

$$\pi_{i,t} = (\tilde{p}_{i,t} - p_t)\tilde{y}_{i,t} - \frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$$

Every period the retailers choose a price to maximize the expected present value of all the future profit:

$$\texttt{Max}_{\tilde{p}_{j,t}} \;\; E_t \sum \Lambda_{t,t+j} \pi_{t+j}$$

which gives the following New Keynesian Phillips curve:

$$log\pi_t = \frac{\gamma - 1}{\psi} log\frac{p_t}{p*} + \beta\mathbb{E}_t log\pi_{t+1}$$

where $p* = \frac{\gamma-1}{\gamma}$ is the steady state wholesale price, or in other words the marginal cost for retailer firms. The Phillips Curve links the New Keynesian block to the production block through the relative the real wholesale price $p*$ for production firms. If the expectation of future inflation is unchanged, when aggregate demand for the final good Y_t increases, retailers must increase production of their differentiated goods because of the nominal rigidity. This in turn increases demand for the production goods $\tilde{y}_{i,t}$, which increases the real wholesale price p_t and generates inflation through the Phillips curve.

B.2.3 Details on the propositions

Proposition 5. *The **New Keynesian Phillips curves** is*

$$log\Pi_t = \frac{\gamma - 1}{\psi} log\frac{p_t}{p^*} + \beta\mathrm{E}_t log\Pi_{t+1}$$

where $p^\star = \frac{\gamma-1}{\gamma}$ is the steady state wholesale price.

Proof. The optimal condition for the price-setting rule is

$$(\gamma-1)\left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma}\frac{Y_t}{P_t} = \gamma\frac{p_t}{P_t}\left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma-1}\frac{Y_t}{P_t} - \psi\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)\frac{Y_t}{\tilde{p}_{i,t-1}} + \mathbb{E}_t\psi\Lambda_{t,t+1}\left[\left(\frac{\tilde{p}_{i,t+1}}{\tilde{p}_{i,t}} - 1\right)\frac{\tilde{p}_{i,t+1}}{\tilde{p}_{i,t}}\frac{Y_{t+1}}{\tilde{p}_{i,t}}\right]$$

With the symmetric assumption $\tilde{p}_{i,t} = \tilde{p}_{j,t} = P_t$, the above equation can be written as

$$(\gamma - 1) = \gamma\frac{p_t}{P_t} - \psi\pi_t(\pi_t - 1) + \mathbb{E}_t\psi\Lambda_{t,t+1}\pi_{t+1}(\pi_{t+1} - 1)\frac{Y_{t+1}}{Y_t}$$

which gives the Phillips curves:

$$(\pi_t - \bar{\pi})\,\pi_t = \frac{\gamma}{\psi}\left(p_t^w - \frac{\gamma - 1}{\gamma}\right) + \mathbb{E}_t\Lambda_{t,t+1}\pi_{t+1}(\pi_{t+1} - \bar{\pi})\frac{Y_{t+1}}{Y_t}$$

where $p_t^w = \frac{p_t}{P_t}$ is the real wholesale price. The log-linearized steady state version of Phillips curves (for computation simplicity) is

$$log\pi_t = \frac{\gamma - 1}{\psi} log\frac{p_t^w}{p^\star} + \beta\mathbb{E}_t log\pi_{t+1}$$

$\square$

Proposition 6. ***Inflation dynamics***

Combining the Euler equation $logR_t + log\beta = log\Pi_{t+1} - log\frac{U'(C_{t+1})}{U'(C_t)}$ *and the Taylor rule* $logR_t + log\beta = \psi_\pi log\Pi_t + \epsilon_t^m$*, we get*

$$\psi_\pi log\Pi_t + \epsilon_t^m = log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right)$$

which is

$$\Pi_t = exp\left(\frac{1}{\psi_\pi}\left[log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right) - \epsilon_t^m\right]\right)$$

Proposition 7. *The optimal conditions for* s *is*

$$\kappa'(s) = \frac{(1-\gamma_m)}{\gamma_m}\theta$$

Proof. In the social planner's problem, the optimal conditions for buyers and sellers are:

$$-V_n m_b = -u_l$$

and

$$-V_n m_s = -u_l \kappa'(s)$$

Combining these two equations gives

$$\frac{m_s}{m_b} = \frac{b}{s}\frac{(1-\gamma_m)\eta}{\gamma_m\eta} = \kappa'(s)$$

which is

$$\kappa'(s) = \theta\frac{1-\gamma_m}{\gamma_m}$$

$\square$

Proposition 8. *The optimal conditions for* ς *is*

$$w = \mu(\theta, s)\varsigma$$

Proof. Define $w = \frac{u_l}{u_c}$ and $v_n = \frac{V_n}{u_c}$

The optimal condition for buyers can be rewritten as

$$w = \eta'(\theta, s) v_n$$

The optimal condition for sellers can be rewritten as

$$\kappa'(s) = \frac{V_n}{u_c}\frac{u_c}{u_l} m_s = \frac{v_n}{w} m_s$$

Multiply w and divided by $\eta(\theta, s)$ on both sides give

$$\frac{w\kappa'(s)}{\eta(\theta, s)} = \frac{m_s v_n}{\eta(\theta, s)} = (1 - \gamma_m)\eta v_n$$

Rearrange the above equation gives

$$\frac{w\kappa'(s)}{\eta(\theta, s)} + \gamma_m \eta v_n = \frac{w\kappa'(s)}{\eta(\theta, s)} + \frac{\theta\eta_\theta(\theta, s)}{\eta(\theta, s)} v_n = \eta v_n$$

Define $\varsigma = \frac{\theta\eta_\theta(\theta,s)}{\eta(\theta,s)} v_n$ and combine with $w = \eta_\theta(\theta, s) v_n$ gives

$$w = \mu(\theta, s)\varsigma$$

$\square$

C Details on the Numerical Solution

C.1 Finite State Markov-Chain Approximations to AR(1) Process with Extrapolative Expectation

This session describes a procedure for finding a discrete-valued Markov chain whose sample paths approximate well those of a AR(1) with extrapolative expectation.

Let z_t be generated by AR(1),

$$z_t = \mu + \rho z_{t-1} + \epsilon_t \tag{36}$$

where ϵ_t is a white noise process with variance σ^2. Let the distribution function of ϵ_t be $Pr[\epsilon_t] = F(\mu/\sigma)$, where F is a cumulative distribution with unit variance. Let $\bar{z}^1 < \bar{z}^2 < ... < \bar{z}^N$ denote the discrete values that the process $\tilde{z}$ approximates the continuous process.

Let $\bar{z}^N$ be a multiple m of the unconditional standard deviation $\sigma_z = \sqrt{\frac{\sigma^2}{1-\rho^2}}$. Then let $\bar{z}^1 = -\bar{z}^N$, and let the remaining be equispaced over the interval $[\bar{z}^1, \bar{z}^N]$.

The extrapolative expectation is modeled as

$$\mathbb{E}_t^{\nu}(z_{t+1}) = \rho_z z_t + \nu\rho(z_t - \rho z_{t-1}) \tag{37}$$

The method for calculating the transition matrix under the extrapolative expectation $p_{ji \to kj} = Pr\{\tilde{z}_t = \bar{z}^k | \tilde{z}_{t-1} = \bar{z}^j, \tilde{z}_{t-2} = \bar{z}^i\}$ follows. Put $w = \tilde{z}^k - \tilde{z}^{k-1}$. For each j, if k is between 2 and $N-1$, set

$$\begin{aligned} p_{ji \to kj} &= Pr\left[\bar{z}_{t+1}^k - w/2 \leq \mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i) + \epsilon_{t+1} \leq \bar{z}_{t+1}^k + w/2\right] \\ &= Pr\left[\bar{z}_{t+1}^k - w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i)) \leq \epsilon_{t+1} \leq \bar{z}_{t+1}^k + w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i))\right] \\ &= F\left(\frac{\bar{z}_{t+1}^k + w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i))}{\sigma}\right) - F\left(\frac{\bar{z}_{t+1}^k - w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i))}{\sigma}\right) \end{aligned} \tag{38}$$

When $k = 1$,

$$p_{ji \to 1j} = F\left(\frac{\bar{z}_{t+1}^1 + w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i))}{\sigma}\right) \tag{39}$$

When $k = N$,

$$p_{ji \to Nj} = 1 - F\left(\frac{\bar{z}_{t+1}^N - w/2 - (\mu + \rho\bar{z}_t^j + \rho\nu(\bar{z}_t^j - \rho\bar{z}_{t-1}^i))}{\sigma}\right) \tag{40}$$

C.2 Steady State Equilibrium

I first solve the model without aggregate uncertainty for its steady state equilibrium. I discretize the state space $S = (z, z_{-1}, m, k)$ into $n_z \times n_z \times n_m \times n_k$ grid points. I then discretize the rational and perceived diagnostic transitions of the exogenous states according to Tauchen (1986).

In the steady state equilibrium, the discount factor is β, the inflation rate is $\Pi^\star = 1$ and the wholesale price is $p^\star = \frac{\gamma-1}{\gamma}$. The nominal and the real rate is therefore $1/\beta - 1$.

1. Given the steady state interest rate, inflation rate and wholesale price, guess a wage rate.
2. Given the prices, I use standard dynamic programming value function iteration with Howard policy improvement to solve the extrapolative firm's Bellman Equation for value function $V^\nu(S)$ and then policy functions for intangible and physical investment $s^\nu(S)$ and $i^\nu(S)$.
3. Compute the Ergodic distribution $\phi(S)$ implied by the firm policies.
4. Check the labor market clearing condition and update the wage rate.

After the convergence, I have the stationary equilibrium aggregate prices $\{\pi^\star = 1, \Lambda^\star = \beta, p^\star = \frac{\gamma-1}{\gamma}, R^\star = 1/\beta, w^\star = w^\star\}$, aggregate quantities $\{C^\star, L^\star, Y^\star, M^\star, K^\star, I^\star, s^\star\}$, firm value function $V^\star(S)$, policy functions $I^\star(S), s^\star(S), \varsigma^\star(S), L_p^\star(S), D^\star(S)$ and stationary distribution $\phi(dS)$.

C.3 Transition Dynamics

The key assumption of the transition dynamics is that after a sufficiently long enough time, the economy will always converge back to its initial stationary equilibrium after any temporary and unexpected (MIT) shocks.

1. Generate a one-time interest rate shock and assume the shock follows $\epsilon^m_{t+1} = \rho^m \epsilon^m_t$ with $\rho^m = 0.5$. Fix a sufficient long transition period from $t = 1$ to $t = T$.
2. Guess a time path for marginal utility $U'(C_t)$ for $t = 1, 2, ..., T+1$ and set $U'(C_{T+1}) = U'(C^\star)$.
3. Set all the prices p, w, R, r in period $T+1$ to be their steady state values. Given the inflation dynamics, obtain R_t from the Taylor rule, r_t from the Fisher equation, w_t from the labor market clearing condition and p_t from Phillips curve for $t = 1, 2, ..., T$.
4. I assume steady state value and policy function in period $T+1$ and update the value and policy functions using **backward induction** given the prices series for $t = 1, 2, ..., T$.
5. Given the policy functions and the steady state distribution as the initial distribution, I use **forward simulation** with the non-stochastic simulation in Young (2010) to find the transition matrix T_t and distribution $\phi_t(d\mathbf{s})$ for $t = 1, 2, ..., T$.

6. I obtain all the aggregate quantities along the time path using $\phi_t(dS)$ and update $U'(C_t)$ using consumption good market clearing condition, as well as other prices series for $t = 1, 2, ..., T$.

C.4 Simulation

D Robustness Check

In the Appendix D, I perform four sets of robustness checks. I first check the robustness regarding firm-level heterogeneity. To confirm that extrapolation bias did drive the heterogeneity in investment sensitivities, I further control for interactions of monetary shocks with other firm-level covariates such as past sales growth, size, leverage, liquidity and intangibility. Results can be found in section D.1 Table A.3 and A.4. It suggests that the differential responses in investment by forecast errors are not driven by firms' heterogeneous financial or liquidity positions.

The second set of results repeat the same exercises in the main analysis but using different measures of monetary shocks including raw changes in fed funds rates and policy news shocks from Nakamura and Steinsson (2018). Table A.5 reports the results using fed funds rates and policy news shock from Nakamura and Steinsson (2018), respectively.

I also verify that the main results are robust to different assumed values of customer capital depreciation rate. In Table A.7, the coefficient estimates for customer capital investment remain statistically and economically significant when the assumed annual depreciation rate varies between 0.15 and 0.3, although the economic magnitude is increasing in the depreciation rate.

In the last set of results, I show that the heterogeneous investment sensitivities are not driven by business cycle effects, as the coefficient estimates of the interaction of previous forecast error and the current GDP growth are mostly insignificant. The results can be found in Table A.8.

D.1 Other Channels

Table A.3: Interaction With Other Firm-Level Covariates: Manager Forecast Error

This table shows results from estimating variants of the baseline specification

$$\begin{aligned}\Delta \log y_{i,t+1} =& \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ &+ \mu X_{i,t-1}\epsilon_t^m + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t+1}\end{aligned}$$

where Forecast $\text{Error}_{i,t-1}$ is the manager's lagged earning forecast error and $X_{i,t-1}$ is firm's lagged size, leverage, liquidity, past sales growth and intangibility. All other variables are defined in the main text, except that $Z_{i,t-1}$ additionally includes the variable $X_{i,t-1}$. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. ${}^{*}p < 0.1$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

	Physical Capital Investment	Customer Capital Investment	Real Sales Growth
		Size	
$\epsilon_t^m \times FE_{t-1}$	-1.15**	-0.58***	-4.54***
	(0.56)	(0.13)	(1.55)
$\epsilon_t^m \times Size_{t-1}$	-0.88	0.68*	-0.34
	(1.11)	(0.36)	(3.79)
Observations	33788	33122	33790
R^2	0.196	0.617	0.174
		Leverage	
$\epsilon_t^m \times FE_{t-1}$	-1.20**	-0.52***	-4.43***
	(0.56)	(0.13)	(1.61)
$\epsilon_t^m \times Leverage_{t-1}$	-0.16	0.47**	1.26
	(0.81)	(0.20)	(2.20)
Observations	33788	33122	33790
R^2	0.196	0.618	0.175
		Liquidity	
$\epsilon_t^m \times FE_{t-1}$	-1.26**	-0.53***	-4.37***
	(0.56)	(0.13)	(1.60)
$\epsilon_t^m \times Liquidity_{t-1}$	0.98	-0.44	-2.40
	(1.10)	(0.28)	(2.00)
Observations	33788	33122	33790
R^2	0.196	0.617	0.174
		Past Sales Growth	
$\epsilon_t^m \times FE_{t-1}$	-1.17**	-0.55***	-4.55***
	(0.56)	(0.13)	(1.55)
$\epsilon_t^m \times SaleGrowth_{t-1}$	-0.57	-0.89*	-0.55
	(1.34)	(0.52)	(8.05)
Observations	33788	33122	33790
R^2	0.196	0.618	0.174
		Intangibility	
$\epsilon_t^m \times FE_{t-1}$	-1.17**	-0.60***	-4.70***
	(0.57)	(0.13)	(1.50)
$\epsilon_t^m \times \frac{xsga}{sales}{}_{t-1}$	0.34	0.02	0.90
	(0.99)	(0.72)	(2.35)
Observations	33786	33120	33788
R^2	0.196	0.625	0.204
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time sector FE	yes	yes	yes
Time clustering	yes	yes	yes

Table A.4: Interaction With Other Firm-Level Covariates: Analyst's LTG Forecast Error

This table shows results from estimating variants of the baseline specification

$$\begin{aligned}\Delta \log y_{i,t+1} =& \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1}\epsilon_t^m \\ &+ \mu X_{i,t-1}\epsilon_t^m + \gamma \text{Forecast Error}_{i,t-1}\Delta GDP_{t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t+1}\end{aligned}$$

where Forecast $\text{Error}_{i,t-1}$ is the analyst's lagged earning growth forecast error and $X_{i,t-1}$ is firm's lagged size, leverage, liquidity, past sales growth and intangibility. All other variables are defined in the main text, except that $Z_{i,t-1}$ additionally includes the variable $X_{i,t-1}$. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Physical Capital Investment	Customer Capital Investment	Real Sales Growth
		Size	
$\epsilon_t^m \times FE_{t-1}$	-1.13***	-0.12	-2.09***
	(0.41)	(0.23)	(0.74)
$\epsilon_t^m \times Size_{t-1}$	0.24	0.81**	0.01
	(0.75)	(0.38)	(1.00)
Observations	138764	134171	138831
R^2	0.177	0.518	0.145
		Leverage	
$\epsilon_t^m \times FE_{t-1}$	-1.31***	-0.38**	-2.04**
	(0.33)	(0.16)	(0.83)
$\epsilon_t^m \times Leverage_{t-1}$	1.59***	0.46	-0.79
	(0.35)	(0.29)	(0.66)
Observations	138764	134171	138831
R^2	0.177	0.518	0.145
		Liquidity	
$\epsilon_t^m \times FE_{t-1}$	-1.26***	-0.40**	-2.01**
	(0.31)	(0.16)	(0.82)
$\epsilon_t^m \times Liquidity_{t-1}$	-0.95	-0.87***	1.35
	(0.70)	(0.24)	(1.02)
Observations	138764	134171	138831
R^2	0.177	0.518	0.145
		Sales Growth	
$\epsilon_t^m \times FE_{t-1}$	-1.20***	-0.35**	-2.12**
	(0.33)	(0.17)	(0.83)
$\epsilon_t^m \times SaleGr_{t-1}$	-0.10	-0.02	2.66
	(0.27)	(0.20)	(3.69)
Observations	138764	134171	138831
R^2	0.177	0.518	0.145
		Intangibility	
$\epsilon_t^m \times FE_{t-1}$	-1.23***	-0.31*	-1.97**
	(0.32)	(0.17)	(0.75)
$\epsilon_t^m \times \frac{xsga}{sales}_{t-1}$	0.10	-0.45*	1.56*
	(0.51)	(0.26)	(0.94)
Observations	138735	134166	138802
R^2	0.179	0.526	0.162
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time sector FE	yes	yes	yes

D.2 Other Measures of Monetary Shocks

Table A.5: Analyst's LTG Forecast Error and Policy News Shock

Results from estimating variants of the baseline specification

$$\Delta y_{i,t+1} = \alpha_i + \gamma_{s,t} + \beta_h ForecastError_{i,t-1}\epsilon_t^m + \Gamma_1' Z_{i,t-1} + \epsilon_{i,t}$$

where ϵ_t^m is policy news shock of Nakamura and Steinsson (2018). All other variables are defined in the main text. The sample is from 1995-2018. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Physical Capital Investment			Customer Capital Investment			Real Sales Growth		
$\epsilon_t^m \times FE_{t-1}$	-1.25***	-1.26***	-1.31***	-0.47**	-0.47**	-0.36	-1.06	-2.14**	-1.49
	(0.44)	(0.44)	(0.45)	(0.22)	(0.22)	(0.25)	(1.10)	(1.00)	(1.11)
ϵ_t^m			-0.56			-1.14			8.89**
			(1.23)			(0.93)			(3.75)
Observations	146609	138764	138766	141927	134225	134227	146886	138831	138833
R^2	0.155	0.177	0.156	0.516	0.540	0.487	0.105	0.145	0.125
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A.6: Analyst's LTG Forecast Error and FF4 shock (Gertler and Karadi (2015))

Results from estimating variants of the baseline specification

$$\Delta y_{i,t+1} = \alpha_i + \gamma_{s,t} + \beta_h ForecastError_{i,t-1}\epsilon_t^m + \beta_z z_{i,t-1}\epsilon_t^m + \Gamma_1' Z_{i,t-1} + \epsilon_{i,t}$$

where ϵ_t^m is monetary shock of Gertler and Karadi (2015). All other variables are defined in the main text. The sample is from 1990-2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Physical Capital Investment			Customer Capital Investment			Real Sales Growth		
$\epsilon_t^m \times FE_{t-1}$	-0.02***	-0.02**	-0.02***	-0.01***	-0.01**	-0.01*	-0.03*	-0.04**	-0.03*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)
ϵ_t^m			-0.01			-0.01			0.20***
			(0.02)			(0.01)			(0.07)
Observations	125352	118528	118530	120620	114028	114030	125618	118625	118627
R^2	0.161	0.185	0.169	0.524	0.554	0.508	0.101	0.138	0.123
Firm controls	no	yes	yes	no	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	no	yes	yes	no	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes	yes

D.3 Various Customer Capital Depreciation Rates

Table A.7: Different Values of Customer Capital Depreciation Rates

This table shows results from estimating variants of the baseline specification

$$\Delta \log y_{i,t+1} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \beta \text{Forecast Error}_{i,t-1} \epsilon_t^m + \gamma \text{Forecast Error}_{i,t-1} \Delta GDP_{i,t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t+1}$$

but with different assumed values of customer capital depreciation rate. The depreciation rate varies between 0.15 and 0.30. All other variables are defined in the main text. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) $\delta_n = 0.15$	(2) $\delta_n = 0.20$	(3) $\delta_n = 0.25$	(4) $\delta_n = 0.30$
	Panel A: Manager's Forecast Error			
$\epsilon_t^m \times FE_{t-1}$	-0.50***	-0.56***	-0.61***	-0.66***
	(0.12)	(0.13)	(0.15)	(0.16)
FE_{t-1}	0.001	0.001**	0.001**	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	33122	33122	33122	33122
R^2	0.653	0.617	0.587	0.560
	Panel B: Analyst's Forecast Error			
$\epsilon_t^m \times FE_{t-1}$	-0.34**	-0.34**	-0.38**	-0.40**
	(0.16)	(0.17)	(0.18)	(0.19)
FE_{t-1}	-0.003***	-0.003***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	134171	134171	134171	134171
R^2	0.556	0.540	0.484	0.455
Firm controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes

D.4 Business Cycle Effects

Table A.8: Heterogeneous Cyclical Sensitivities

This table shows results from estimating the following specification:

$$\Delta \log y_{i,t+1} = \alpha_i + \alpha_{s,t} + \lambda \text{Forecast Error}_{i,t-1} + \gamma \text{Forecast Error}_{i,t-1} X_t + \Gamma' Z_{i,t-1} + \epsilon_{i,t+1}$$

where X_t is either ΔGDP_t or UNEMP_t, a measure of business cycle. The sample covers from 1984 to 2021. All other variables are defined in the main text. The firm and sector-quarter fixed effect are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at both the firm and time level, and t statistics in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Physical capital investment		Customer capital investment		Real Sales Growth	
$\Delta\text{GDP}_t \times FE_{t-1}$	-0.018	-0.013	-0.010	-0.008	0.108*	0.106*
	(0.018)	(0.020)	(0.009)	(0.010)	(0.059)	(0.061)
FE_{t-1}	-0.005***	-0.005***	-0.003***	-0.003***	0.001	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	221486	207475	212899	199480	221998	207683
R^2	0.143	0.165	0.451	0.470	0.110	0.154
$\text{UNEMP}_t \times FE_{t-1}$	-0.000**	-0.000	-0.000	-0.000	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FE_{t-1}	-0.003**	-0.004***	-0.003***	-0.002***	0.005***	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	221486	207475	212899	199480	221998	207683
R^2	0.143	0.165	0.451	0.470	0.110	0.154
Firm controls	no	yes	no	yes	no	yes
Firm FE	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes