Cash flow duration, financial constraints, and the stock market sensitivity to monetary policy*

Eric Offner
Universität Hamburg

July 30, 2023

Abstract

An open question in macro-finance concerns the differing reactions of growth and value stocks to monetary policy. I address this question using a high-frequency event-study and find that growth stocks respond significantly more to policy surprises. This finding is consistent across single stocks, portfolios, and stock indexes and persists for several days post-FOMC announcement. I show that these results are driven by a combination of heterogeneity in cash flow duration and distinct effects of monetary policy on the risk premium. In contrast, financial constraints explain the heterogeneity only when accounting for cash flow duration. These empirical findings can be explained by a reduced-form asset pricing model in which firms heterogeneity is given by cash flow duration.

Keywords: FOMC, monetary policy, stock market, cash flow duration, financial constraint
JEL Classifications: E44, E52, E58

*I thank Michael Bauer, Refet Gürkaynak, Daniel Huber, Hatice Gökçe Karasoy-Can, Sang Seok Lee, Michael McMahon and participants of the Universität Hamburg PhD Seminar for valuable comments. All remaining errors and all views expressed in the paper are mine and are not necessarily those of the individuals or groups listed above.

1 Introduction

The connection of monetary policy, stock returns, and firms' fundamentals is of first-order importance for better understanding policy transmissions and asset prices movements. Despite extensive research on the fundamental differences between growth and value stocks, less is known about their sensitivity to monetary policy. While the asset pricing literature has mainly focused on attempting to explain the value premium, the macro-finance literature has provided conflicting evidence on the way growth and value stocks respond to monetary policy (Ehrmann and Fratzscher, 2004; Maio, 2014). Yet, given the extensive evidence on the distinct characteristics of growth and value stocks one would expect that they respond differently to monetary policy.

To illustrate this point Figure 1 shows the path of the Dow Jones Industrial Average (DJIA), NASDAQ and the 1-year treasury yield since the end of 2021. In this period, which is characterized by four FOMC announcements, the stock market correlates negatively with the 1-year treasury yield. The underperformance of the NASDAQ relativ to DJIA amounts to around -15%. Figure 1 conveys the impression that growth stocks react more to monetary policy. Indeed, during the period shown in Figure 1 the NASDAQ has a price-to-book ratio of 5.7 compared to 4.6 of the DJIA. Nevertheless, Figure 1 does not provide causal evidence of monetary policy on stock returns, since other factors could have driven the stock prices and the yields.

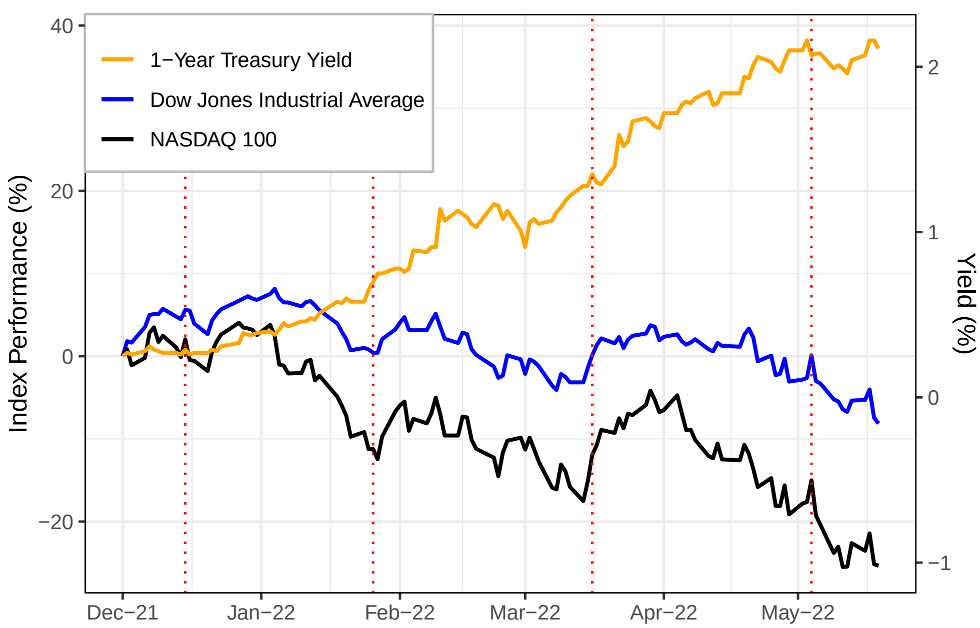
This paper uses a high-frequency approach to provide new evidence that growth stocks exhibit a greater sensitivity to monetary policy than value stocks. The estimated difference is statistically and economically significant and is observed at the index level, individual stock level, and across portfolio sorts, suggesting that this result does not disappear due to idiosyncratic noise or diversification. Furthermore, I show that after a monetary policy surprise a significant larger response of growth stock relative to value stocks will persist on average for several days. Yet, a monthly analysis is not well suited to capture these causal effects, which is one of the reasons previous studies have failed to find the same result.

A plausible reason why growth stocks are more sensitive is that they are longer duration assets. As their cash flow payments are, on average, further away in the future, any change in discount rates will have a more pronounced impact on their prices. This is a natural explanation, as several studies have confirmed that cash flow duration can explain the value premium (Lettau and Wachter, 2007; Gonçalves, 2021; Gormsen and Lazarus, 2023).

While the duration argument is widely accepted among industry professionals (Swedroe, 2019), it has yet to be investigated in academic studies of the stock market's response to monetary policy. Previous studies have instead focused on the impact of monetary policy on firms through the lens of cash flow fundamentals. For example, Maio (2014) argues that value stocks should respond stronger to monetary policy, because of the credit channel mechanism through which monetary policy transmissions to investment operates. The balance sheet channel states that after a monetary policy easing, firm's net worth increases due to a higher collateral value. The bank lending channel operates through the fact that banks increase their loan supplies after a monetary policy easing providing firms with more access to loans. Both channels enable firms to increase investment, and ultimately future cash flows. Yet, these explanations imply that monetary policy impacts firms differently depending on their vulnerability to external funds. Chava and Hsu (2020) show in an empirical study that financially constrained firms are more sensitivity to monetary policy.

While the idea that financial constraints explain the responses to monetary policy is plausible, it remains unclear whether growth or value stocks are more financially constrained. On the one hand, a variety of investment opportunities might force growth stocks to be more reliant on external funding and thus more financially constrained. On the other hand, growth stocks might have more favourable conditions in the credit market due to their higher asset valuation.

Figure 1: Negative Correlation of Yields and Stock Market



The figure shows the 1-year treasury yield on the right y-axis and the performance of the Dow Jones Industrial Average and NASDAQ 100 Index on the left y-axis. The red vertical dotted line represent the FOMC announcements. The sample goes from Dec-2021 to May-2022.

Given that cash flow duration and financial constraints are the two most widespread economic explanations for the different reactions of growth and value stocks, I focus on examining the effects of these two variables. Specifically, I run a panel regression of firm-level stock returns on market-to-book equity, monetary policy surprises, and measures of duration and financial constraint. I find that cash flow duration is the main driver of growth and value stock sensitivity to monetary policy. Measures of financial constraints do help explaining firms' heterogeneity, however, they do not seem to be linked to the responses of growth and value stocks.

The interaction of financial constraints with cash flow duration and monetary policy is significantly different from zero, implying an indirect effect of financial constraints on growth and value stocks. Specifically, after a monetary policy shock the cash flow of financially constrained firms respond stronger to monetary policy. This causes growth stocks to respond more because this effects gets multiplied by the cash flow duration.

A natural step when analysing movements in stock prices is to run a Campbell & Shiller decomposition. I follow Bernanke and Kuttner (2005) and log-linearize the reactions of stocks returns to monetary policy. This method allows the decomposition of unexpected return responses to monetary policy in revisions to investors' future expected real rates, discount rates, and dividends, shedding more light in the drivers of the sensitivity of both groups of stocks. Specifically, breaking down the discount rate effects in risk-free rate and future excess returns helps understanding whether the effects of monetary policy that are accounted by duration come mainly from changes in risk-free rate or the risk premium. Moreover, changes in investors' cash flow expectations might not be driven solely by financial constraints, but by other factors no accounted by in the panel regression. The Campmbell & Shiller decomposition gives the overall sensitivity of cash flow news to monetary policy.

The stock return decomposition confirms that real rates play a relatively minor role when it comes to affects of policy surprises on stock returns, a fact previously documented by Bernanke and Kuttner (2005). The decomposition shows large differences in the revisions of future risk premium of growth and value stocks on both aggregate and portfolio levels. Specifically, the risk premium of growth stocks are more strongly revised after a monetary policy surprise. Moreover, on the aggregate level value stocks seem to have higher exposure to cash flow news, but this exposure is not enough to counteract the discount rate effects. In general, this analysis shows that the difference in risk premium could also be responsible for different sensitivities of growth and value stocks.

To explain these new empirical findings in a conceptual framework, I build upon the reduced-form asset pricing model from Lettau and Wachter (2011). The model implies that firms heterogeneity is generated solely by the timing of the cash flow payment, which enables to capture the duration effects from monetary policy shocks. I calibrate the model using the results of the stock return decomposition on the S&P500 and construct two aggregate portfolios based on the timing of the cash flows. I show that the market duration implied by the model is close to the estimated duration by Weber (2018) and Gonçalves (2021) and that the sensitivities of the growth and value portfolios to monetary policy are very similar to my empirical results.

I provide substantial new evidence on the responses of growth and value stocks to monetary policy and explain the economic reasoning behind these sensitivity. My results have strong implications for the monetary economics literature, as it shows that cash flow duration is an important mechanism through which monetary policy spreads to the equity market. It also confirms the credit channel implied by different economic models, although these are unrelated to growth and value stocks.

Related Literature

The duration argument has little empirical support in the macro-finance literature, and the evidence on the financial constraints is conflicting. For example, Maio (2014) studies the monthly relation of monetary policy and market-to-book equity and finds that value stocks are relatively more reactive. He argues that because a low-equity valuation ratio is a result of negative shocks in past cash flows, value firms should be more financially constrained.

In contrast to this study is the work of Ehrmann and Fratzscher (2004). They document that growth firms (firms with higher Tobin's q) are more reactive. Yet, they do not argue in favour of a duration effect, but also from a financial constraint point of view: "a high q indicates that ample investment opportunities are present for which may imply, ceteris paribus, that this firm has higher financial constraints requiring more external funds to finance this investment."

To interpret the results from Maio (2014) and Ehrmann and Fratzscher (2004), which are the two reference points in this study, their limitations need to be addressed. Ehrmann and Fratzscher (2004) use a relatively low sample of 79 FOMC meetings. Their sample is composed only of S&P500 firms, which can lead to survival bias. Maio (2014) proxies policy shocks with monthly changes in federal funds rates. Hence, his results are susceptible to the endogeneity bias of monetary policy. Finally, both papers carry out solely portfolio analysis. It is not clear whether the results hold for single stocks.

The evidence in my study is robust to all aforementioned limitations. First, the sample goes from 1990 to 2018 and covers almost 30 years of monetary policy data. Second, I use a high-frequency approach and account only for the surprise component of monetary policy, avoiding the endogeneity bias. Third, the survival bias is avoided by considering the whole universe of stocks from CRSP and Compustat.[1] Fourth, I run a collection of robustness checks which confirm the validity of the results. Using fixed effects I show that the regressions are not confounded by time or cross-sectional unobserved effects, such as higher valuation periods. Portfolio sorts confirm that idiosyncratic noise does not affect the estimation. Finally, repeating the analysis with Fama and French portfolios confirms that the results are independent of my sample and pre-processing choice.

More recently, new empirical studies of the effects of monetary policy surprises on the cross-section of returns have gained more attention. Particularly, a variety of papers have analyzed how responses to monetary policy depends on financial constraints. Chava and Hsu (2020) use high-frequency monetary policy surprises to show that financial constrained firms are more reactive to monetary policy. Their result contradicts the previous study of Ozdagli (2018) who finds the exact opposite. Gürkaynak et al. (2022) show that cash flow exposure explains a great portion of variation of stock returns responses to monetary policy. They use the financial constraint measure developed by Schauer et al. (2019) to show that more financially constrained firms have a larger sensitivity to cash flows in response to monetary policy shocks. With regards to financial constraints and investment, Cloyne et al. (2023) develop a measure of financial constraints based on age and dividend payment and find that one third of investment response to monetary policy is due to financial frictions.

My study is also related to a vast literature of empirical studies of equity duration (Cornell, 1999; Dechow et al., 2004; Da, 2009; Weber, 2018; Gonçalves, 2021; Chen, 2022; Gormsen and Lazarus, 2023). This paper build upon the duration measure proposed by Gonçalves (2021). He uses it to document new evidence on the short duration premium. The paper of Chen (2022) is closely related to mine. He uses high-frequency monetary policy identification to create a measure of effective equity duration by considering, not only discount rate effects, but also cash flow effects. The main difference, however, is that I am interested in the economic channels of the policy surprises and how these effect the cross-sectional of stock returns.

For the conceptual framework I build upon the model from Lettau and Wachter (2011). There is a vast amount of models proposed to explain the equity term structure and equity duration. For a great overview of the literature I refer to Van Binsbergen and Koijen (2017). To the best of my knowledge there is no theoretical model that attempts to explain the monetary policy responses of stock prices through cash flow duration.

The results in this paper can also be linked to studies that explain the value premium

[1] While it could be argued that Compustat data is also affected by survival bias, the bias should be weaker than just restricting the sample to the S&P500. See Davis (1996) for a discussion on the survival bias in the Compustat database.

through cash flow fundamentals (Carlson et al., 2004; Zhang, 2005; Liu et al., 2009). The Campbell & Shiller decomposition shows that risk premium and cash flow news are different for growth and value stocks. Although economic models usually try to explain the value premium either entirely through cash flow fundamentals or cash flow duration, this paper can be used as evidence that the truth might lie somewhere in the middle.

Finally, to understand the stock price movements, I build up on the ideas of Campbell and Shiller (1988), Campbell (1991), Campbell and Ammer (1993), and Vuolteenaho (2002). Campbell and Ammer (1993) combine the linear-approximation of the stock price identity derived by Campbell and Shiller (1988) with a VAR to decompose unexpected return movements in discount rate and cash flow news. Vuolteenaho (2002) applies the same logic to the cross-section of stocks. He finds that single stock returns are mainly driven by cash-flow news, but that cash-flow news are diversified away in aggregate portfolios. Contrarily, discount rate news are strongly positive correlated. Bernanke and Kuttner (2005) further decompose returns into real rates, expected discount rate, and cash flows news in the context of high-frequency monetary policy. They find that monetary policy affects stock prices mainly through future excess returns and cash flow and less through real rates. Recently, Chen and Zhao (2009) addressed several limitations of the Campbell & Shiller decomposition. They argue that revisions to discount rates cannot be accurately measured because of low predictive power. My paper carefully addresses this limitation.

2 Data and Summary Statistics

I begin by describing how the surprise elements of monetary policy are extracted and the sample is created. Then, I briefly provide summary statistics which are relevant for further analysis.

2.1 High-frequency data for FOMC announcements

I start with a sample of FOMC announcements which goes from February 1990 to December 2018. The sample entails 255 FOMC announcements, of which 23 were unscheduled.

In order to identify causal links between monetary policy and stock returns I make use of high frequency event studies, a method which goes back to Kuttner (2001). He uses the 30-minutes change in the rate implied by the current-month futures contract after a FOMC announcement. Gürkaynak et al. (2005) extend his approach and use next to the current-month futures, the three-months funds future contract, and the prices of eurodollars future contracts with maturity of up to a year. More recently, Nakamura and Steinsson (2018) proposed to extract only the first principal component of the five instruments. This factor accounts for target and forward guidance shocks and will be used for the analysis in this paper.[2]

2.2 Firm-level Data

I construct an unbalanced panel data sample using quarterly balance-sheet data extracted from Compustat and stock prices from CRSP. The main variable of interest is the market capitalization divided by the book equity of each firm in each quarter. To make sure that market participants include the market-to-book equity in their information set during the FOMC announcements, I lag it by one quarter. For example, for the FOMC announcement of July 30, 2014, I use the balance sheet data published in March 31, 2014. The bottom and top 1 percent of market-to-book equity are trimmed, a common process to reduce effects of outliers also used by Ippolito et al. (2018) and Gürkaynak et al. (2022).

The dependent variable is the simple return computed using the closing prices of the FOMC announcement day and the closing price of the preceding day. In the final sample I include stocks exchanged in the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 (Similar to Fama and French (1993)). To ensure liquidity, stocks with a price less than $5 or a market capitalization less than $10 million are dropped (see, for example, Chava and Hsu (2020)). This gives a total of 514,199 data points from 8,946 different firms.

Table 1 shows that .....

[2] The derivation of the monetary policy surprise is shown in appendix.

Table 1: Summary Statistics

Empirical moments	Mean	SD	Min	q25	Median	q75	Max	Obs.
MB	3.02	3.30	-37.19	1.39	2.19	3.58	67.35	378,758
Size	2.03	1.84	-3.84	0.66	1.96	3.28	7.58	389,840
Prof.	0.03	0.04	-0.42	0.02	0.03	0.05	0.16	360,329
Lev.	0.37	0.26	-0.08	0.16	0.34	0.52	2.05	381,835
Duration	57.83	51.74	1.35	35.58	48.24	63.80	500.04	274,053
FC constraint	0.50	0.50	0	0	0	1	1	312,885

Correlation	MB	Size	Prof.	Lev.	Duration	FC
MB	1	0.09	0.16	0.12	0.22	-0.20
Size	0.09	1	0.05	0.31	0.09	-0.39
Prof.	0.16	0.05	1	-0.08	-0.19	-0.17
Lev.g	0.12	0.31	-0.08	1	0.31	0.28
Duration	0.22	0.09	-0.19	0.31	1	0.07
FC	-0.20	-0.39	-0.17	0.28	0.07	1

This table shows the summary statistics of following accounting/control variables: Market to book equity, size, profitability, leverage, duration, and financial constraint. The quarterly dataset of market to book equity, size, profitability, and leverage was extracted from Compustat and span the period from 1990 to 2018. I obtained yearly firm level cash flow duration from Gonçalves (2021) and the financial constraint was constructed according to Schauer et al. (2019) and uses accounting data from Compustat.

2.3 Aggregate Data

To investigate the effects of policy surprises on aggregate measures of valuation and stock returns, I extract daily prices for the S&P500, the Russel 1000 and the Russel Growth and Value Index as well as the corresponding quarterly aggregate multiples from Bloomberg. Table 2 shows the summary statistics of the four stock indexes.

Table 2: Summary statistics of surprises, returns and valuation ratios

	Variable	Mean	SD	Max	Min	Nr. of Obs.
Monetary policy surprise		−0.01	0.04	0.08	−0.26	259
S&P500	Return	0.30	1.19	5.14	−2.94	259
	P/B	2.82	0.75	5.04	1.74	116
	P/E	19.53	4.03	29.88	12.68	116
Russel 1000	Return	0.30	1.19	5.26	−2.97	259
	P/B	2.73	0.77	4.69	0.004	96
	P/E	19.84	4.15	30.88	12.22	96
Russel Value	Return	0.30	1.18	5.74	−3.38	248
	P/B	2.07	0.45	3.16	1.25	96
	P/E	17.06	3.04	29.01	11.28	96
Russel Growth	Return	0.36	1.36	9.76	−3.42	248
	P/B	5.01	1.52	9.76	2.75	96
	P/E	24.62	9.29	63.30	12.54	96

The table reports the summary statistics of monetary policy surprises, one-day stock returns and valuation multiples for the fourth stock market indexes. The sample goes from January 1990 to December 2018.

In contrast to the S&P500, which has valuation data available from the beginning of 1990, the Russel Indexes have valuation ratios starting from 1995. Hence the lower number of observations. The growth index has higher valuation ratios than the value index. The mean P/B ratio is about two times as high as the P/B ratio of the value index and the standard deviation even three times as high. The growth index has higher average return for the observed period, implying that the value premium was slightly negative. The S&P500 and the Russel 1000 Index are very similar and lie somewhere in between the growth and value extremes, but closer to the value index.

3 Differences in growth and value stocks

3.1 One-day Analysis

3.1.1 Index-level analysis

The section focuses on the effects of policy surprises on the aggregate stock market returns. Panel A of Table 3 shows the regression results of the stock returns on the monetary policy surprise. As the two first columns are proxies for the aggregate market, they revisit the results documented by previous works, such as Gürkaynak et al. (2005), Bernanke and Kuttner (2005), Nakamura and Steinsson (2018) and Gürkaynak et al. (2022). I document statistically significant negative effects of monetary policy surprises on stock returns: Stocks returns decrease around 9.4 percentage points after a one percentage point tightening surprise.

The estimated effect can vary in comparison to other studies, because the sample period and the surprises are not exactly the same. For example, Bernanke and Kuttner (2005) document for the period between 1989 and 2002 a drop of around 4.7 percentage points after a one percentage point tightening surprise. Yet, their surprise measure does not account for forward guidance.

To analyse the policy surprise effects on aggregate growth and value stocks, I use the Russel Value and Growth 1000 Indexes. The last two columns of Table 3 panel A show the results of the one-day returns regression on monetary policy surprises. The estimated coefficients indicate a higher response of growth stocks relative to value stocks. The Russel Growth Index falls by about 12 percentage points after a one percentage point increase in monetary policy surprises, 4 percentage points more than the Russel Value Index. However, the difference in response of the one-day return is not statistically significantly different from zero.

This set up also allows to answer a close related question, namely whether the effects of monetary policy surprises are sensitive to movements of valuations over time. This is an important question, since high market valuations can signal bubbles, which might drive market sensitivity to policy surprises.

To evaluate the effects of the aggregate valuation, I regress the one-day returns on valuations interacted with monetary policy surprises, where valuations are measure by market-to-book equity and price-earnings ratio. Table 3 panel B shows the results for the S&P500 and the Russel Index. The interaction of monetary policy with both valuation measure is not significantly different from zero. Hence, the possibility of stocks being more sensitive on periods of higher valuations can be excluded.

Table 3: Reaction of stock indexes to monetary policy surprises and market-to-book equity

Panel A	S&P500 (Jan-90 - Dec-18)	Russel 1000 (Jan-90 - Dec-18)	Russel Value (Jan-91 - Dec-18)	Russel Growth (Jan-91 - Dec-18)	Growth - Value (Jan-91 - Dec-18)
mps	-9.54^{***}	-9.58^{***}	-7.71^{***}	-11.98^{***}	-4.27
	(2.42)	(2.45)	(2.37)	(3.34)	(2.73)
Constant	0.21^{***}	0.21^{***}	0.22^{***}	0.24^{***}	0.02
	(0.07)	(0.07)	(0.07)	(0.08)	(0.04)
N	259	259	248	248	248
R^2	0.11	0.11	0.08	0.14	0.05
Panel B	S&P500		Russel 1000		
mps	-8.78^{***}	-8.56^{***}	-10.90^{***}	-10.30^{***}	
	(2.31)	(2.48)	(2.94)	(3.41)	
mb*mps	-2.18		0.03		
	(1.80)		(2.36)		
pe*mps		-2.61		-1.33	
		(2.20)		(3.06)	
Observations	256	256	201	201	
R-squared	0.12	0.12	0.12	0.13	

Panel A regresses 1-day stock returns on monetary policy surprises. Panel B estimates the regression $r_t = \beta_0 + \beta_1 \times mps_t + \beta_2 \times val_{t-1} + \beta_3 \times mps_t \times val_{t-1} + \varepsilon_t$. The sample goes from January 1990 to December 2018. mps stands for monetary policy surprise and val for the valuation measure (market-to-book equity or price-earnings ratio). White standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

3.1.2 Panel regressions

Although time-varying valuations do not seem to be a concern, other time or cross-sectional varying variables might cofound the pooled OLS results. In Appendix B I show formally that this can lead to an omitted variable bias, if the unobserved effect is correlated with market-to-book equity and if their interaction is correlated with stock returns. For this reason I include apart from pooled OLS, time and firms fixed effects. The estimated model is:

$$r_{t,i} = \beta_0 + \beta_1 \times mps_t + \beta_2 \times mb_{i,t-1} + \beta_3 \times mps_t \times mb_{i,t-1} + \gamma_i + \alpha_t + \varepsilon_{i,t}$$

where i denotes the firm, t the day of the FOMC announcement, r the stock return, mps the monetary policy surprise, mb the market-to-book equity, and γ and α the fixed effects. In

Appendix B I provide the theory necessary to understand how our regression design avoids the problems of unobserved effects.

Table 4 shows the results of the panel regressions with different specification designs. The first column estimates the effects of policy surprises on single stock returns. I find that a one percentage point increase in monetary policy decreases prices, ceteris paribus, on average 7.5%. The interaction effect of market-to-book equity and monetary policy surprise is statistically significant and also robust towards using firms and time fixed effects. An additional unit of market-to-book equity strengthens the policy response of stock returns by a number between 0.74 and 0.97 percentage points. This means that the stock price of a firm with one standard deviation below the mean market-to-book equity drops on average 5.4% after a 1 percentage point rise in policy surprises. Likewise, a firm with one standard deviation above the mean see its stock price fall on average 9.8%, almost twice as much. These examples highlight the economic significance of the results.

Table 4: Reaction of stock returns to monetary policy surprises and market-to-book equity

	(1)	(2)	(3)	(4)	(5)	(6)
mb		-0.002	-0.02^{**}	-0.001	-0.02^{**}	-0.04^{***}
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
mps	-7.71^{***}	-5.28^{**}	-5.20^{**}			5.16^{***}
	(2.14)	(2.09)	(2.04)			(1.89)
mb*mps		-0.89^{***}	-0.97^{***}	-0.74^{**}	-0.82^{***}	-0.46^{**}
		(0.34)	(0.32)	(0.30)	(0.28)	(0.21)
Constant	0.25^{***}	0.25^{***}				
	(0.06)	(0.06)				
N	533,965	518,678	518,678	518,678	518,678	518,676
R^2	0.003	0.003	0.11	0.03	0.14	0.76
Firms FE	NO	NO	YES	NO	YES	YES
Time FE	NO	NO	NO	YES	YES	NO

The table estimates the regression $r_{t,i} = \beta_0 + \beta_1 \times mps_t + \beta_2 \times mb_{i,t-1} + \beta_3 \times mps_t \times mb_{i,t-1} + \gamma_i + \alpha_t + \varepsilon_{i,t}$ using observations from January 1990 to December 2018. mps stands for monetary policy surprise and mb for market-to-book equity. Column (1) regresses returns on monetary policy surprises, columns (2) to (5) estimate the regression model using pooled OLS and different fixed effects specifications. Column (6) uses beta-adjusted returns. Two-way clustered standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

The fact that the coefficient of the interaction term decreases when time fixed effects is included points to the existence of a time-varying unobserved effect. It also confirms that monetary policy surprises have heterogeneous effects in the cross-section.

Finally, similar to Gürkaynak et al. (2022) column (6) replaces stocks returns by beta-adjusted stock returns (returns minus the expected return according to the CAPM). The interaction term is still negative and significant, yet it decreases in magnitude. The high R^2 indicates that the market-to-book equity explains about three quarters of the firm-level variation in daily stock returns that is not accounted for in the CAPM.

3.1.3 Portfolio-level Results

Several studies advocate the use portfolio sorts when working with cross-sectional stock returns (see, for example, Cochrane (2009)). The reason is that portfolios are less susceptible to idiosyncratic noise. Also, by dynamically adjusting the portfolios each quarter the unobserved effects are no longer a problem. Another advantage is that portfolio sorts enables to discover the presence of non-linear effects.

I group the firms into 10 equal-size portfolios sorted by their lagged market-to-book equity for each quarter in the sample. Table 5 presents the summary statistics of market-to-book equity for each portfolio. Although it would seem obvious to expect a monotonically increasing maximum market-to-book ratio, the maximum value of the first portfolio is, in fact, larger than the maximum from the second portfolio. This is because, in most cases, stocks with negative book equity are assigned to the first decile. Thus, the aggregate book value in the first decile is reduced by the negative book equity, in which case the overall market-to-book value increases. The standard deviation from the last decile is notably larger than in the others, indicating that a lot of the noise in the data comes from this extreme decile.

Figure 2 shows the estimated responses plotted against the mean market-to-book equity for each decile portfolio. The pattern confirms that the surprise response decreases with market-to-book ratio and that this decrease is non-linear. The estimated response seems to converge with increasing mean market-to-book equity.

Table 5: Summary statistics of market-to-book equity sorted portfolios

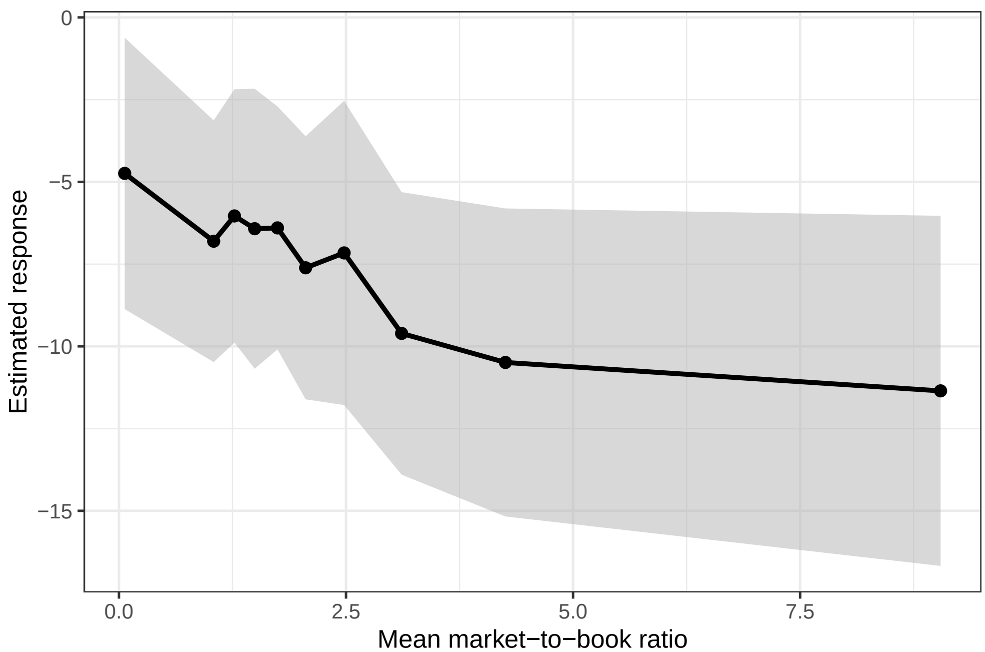
Portfolio	Mean	SD	Max	Min
1	0.93	0.29	2.1	0.34
2	1.04	0.19	1.46	0.57
3	1.27	0.21	1.78	0.71
4	1.49	0.23	2.1	0.87
5	1.75	0.26	2.38	1.05
6	2.06	0.31	2.79	1.26
7	2.48	0.38	3.25	1.52
8	3.12	0.5	4.51	1.91
9	4.23	0.83	6.82	2.67
10	7.83	2.07	13.6	4.88
Overall	2.57	0.61	4.31	1.59

The table calculates the mean, standard deviation, maximum and minimum value of market-to-book equity for each decile portfolio. To calculate them, firms are grouped into 10 equal-size portfolios sorted by their lagged market-to-book equity for each quarter in the sample. For each portfolio I aggregate the market capitalization and divide it by the aggregate book equity in a given quarter. The mean, standard deviation, maximum and minimum from the 10 time-series are shown above. The sample goes from January 1990 to December 2018.

To test whether the reactions of portfolios with higher market-to-book equity are significantly larger in magnitude, I calculate the return of spread portfolios and regress them on the policy surprises. Spread returns are constructed by subtracting the returns of the lowest deciles from the highest. For example, the 30% spread portfolio is the return of a portfolio long on all stocks in the three highest deciles and short on the stocks in the three lowest deciles.

Table 6 shows the regression of the spread portfolios on monetary policy surprises. Columns (1) to (3) show that the 10%, 30% and 50% spread portfolios are in line with the panel regressions: The portfolios with relatively higher average market-to-book equity drop significantly more after a monetary policy tightening surprise. The last two columns demonstrate that the results are not solely driven by a small extreme sample. A portfolio with stocks in the highest 10% spectrum of market-to-book equity (the stocks which are the closest to the growth extremity) react significantly stronger than all others. Likewise, a portfolio with stocks in the lowest 10% spectrum of market-to-book equity (the stocks which are the closest to the value extremity) react significantly less to monetary policy surprises.

Figure 2: Reaction of market-to-book equity sorted portfolios to monetary policy



The figure shows the estimated response of the 10 decile portfolios sorted by market-to-book equity using monetary policy surprises against the mean market-to-book equity of each portfolio. 10% confidence intervals are drawn around the point estimation. The samples goes from January 1990 to December 2018.

In Appendix C I re-run the portfolio analysis using Fama and French portfolios and show that these results are independent of the sample construction. The data was extracted from Ken French's Website. The results provided in Table C.1 are in line with the panel regression and the portfolio sorts.

The fact that the first and last decile portfolios do not seem to be statistically different in Figure 2, but are indeed significant when running the regression in Table 6, might be puzzling. I point out that it is not possible to infer from Figure 2 whether the two portfolios are statistically significantly different. Because the figure does not take into account the correlation between the estimated coefficients, a high correlation can lead to smaller standard errors which makes the results in Table 6 significant.

Table 6: Reaction of spread portfolios to monetary policy surprises

	10% - 10%	30% - 30%	50% - 50%	90% - 10%	10% - 90%
mps	-6.61^{**}	-4.62^{**}	-3.16^{**}	-3.25^{**}	-4.10^{***}
	(3.03)	(1.99)	(1.44)	(1.57)	(1.01)
Constant	-0.18^{**}	-0.07^{*}	-0.04	-0.18^{***}	-0.02
	(0.08)	(0.04)	(0.03)	(0.07)	(0.04)
N	255	255	255	255	255
R^2	0.04	0.07	0.07	0.02	0.06

The table estimates the regression $r_t^s = \alpha + \beta \times mps_t + \varepsilon_{i,t}$ using the sample from January 1990 to December 2018, where r_t^s is the return of the spread portfolio. The spread portfolios are formed by sorting firms according to the market-to-book ratio and subtracting the 50%, 30% and 10% lowest from the highest companies each period. The last two columns show the spread portfolio of the 90% highest companies and the 10% lowest and vice-versa. White standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

3.2 Results Based on Multiple Days

3.2.1 Monthly Analysis: Reconciling with Maio (2014)

Research in asset pricing is conducted to a great extent on a monthly basis. This might be required because of the methods used (for example VAR requires a periodic frequency) or because of data availability. In addition, the conclusion on the first part of the paper, that growth stocks react stronger to monetary policy than value stocks, contradicts the findings of Maio (2014), who finds in a monthly analysis the exact opposite. In order to reconcile my results with his, a study on a monthly frequency is needed.

Instead of high-frequency monetary policy identification, Maio (2014) opt to use the monthly changes in federal funds rates as a monetary policy indicator. The main problem with this approach is that there will be cofounding variables. Monetary policy is highly endogenous, because the Fed does its best to react to economic conditions. The same conditions that affect stock prices.

To revisit the results obtained by Maio (2014), I regress 10%, 20%, and 30% spread portfolios on the first difference of the federal funds rates.[3] Panel A from Table 7 presents the estimated coefficients. Analogous to his study I find a positive significant effect of the change in federal funds rates in the 10% and 20% spread portfolios, which implies that value stocks are more reactive to monetary policy. Panel B re-runs his results starting in 1990, the

[3] This analysis differs slightly from Maio (2014) who uses a second monetary policy indicator, but finds no significant coefficients and runs a Wald test instead of spread portfolio regressions.

same period used in this paper and shows that returns responses from value portfolios are no longer significantly higher than the responses from growth portfolios. Thus, Maio (2014)'s results are sensitive to the sample choice. Panel C shows that his statistically significant findings are present in the whole sample. This could mean that they are driven by the period antecedent the 90s, for example, the great inflation.

Table 7: Reaction of monthly spread portfolios to federal funds rates

Spread portfolio	10%	20%	30%
Panel A: Jul-1963 - Jun-2008			
ΔFFR	77.58**	54.07*	31.11
	(37.21)	(28.23)	(23.41)
Constant	-0.60***	-0.47***	-0.38***
	(0.18)	(0.14)	(0.11)
N	540	540	540
R^2	0.01	0.01	0.005
Panel B: Jan-1990 - Dec-2018			
ΔFFR	-62.11	-69.73	-116.91
	(173.05)	(128.15)	(111.61)
Constant	-0.09	-0.07	-0.03
	(0.25)	(0.19)	(0.15)
N	348	348	348
R^2	0.001	0.001	0.005
Panel C: Jul-1963 - Dec-2018			
ΔFFR	72.08**	50.34*	26.21
	(36.25)	(27.76)	(23.32)
Constant	-0.37**	-0.31**	-0.24**
	(0.18)	(0.13)	(0.11)
N	666	666	666
R^2	0.01	0.01	0.002

The table shows the estimated regression of spread portfolio returns on changes in federal funds rates (FFR). Panel A uses the same sample time period as Maio (2014). Panel B uses the same time period as the other results in this paper and Panel C includes all observations available. Columns (1) to (3) are the returns of the 10%, 20% and 30% spread portfolios, respectively. White standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 8 repeats the regressions from Table 7 using the exogenous monetary policy surprises. The policy surprises are aggregated by summing all surprises within a month. In case of no FOMC announcement within a month, the policy surprise is zero. I find negative, but insignificant effects of policy surprises on the spread portfolio returns. The most plausible explanation for these results is the increase in the noise, which is indicated by the very low R-squared.

Table 8: Reaction of monthly spread portfolios to monetary policy surprises

	10%	20%	30%
mps	−3.71	−3.35	−4.21
	(5.78)	(4.50)	(3.76)
Constant	−0.11	−0.08	−0.04
	(0.26)	(0.19)	(0.16)
N	348	348	348
R^2	0.001	0.001	0.003

The table shows the estimated regression $r_t^s = \alpha + \beta \times mps + \varepsilon_{i,t}$. r_t^s is the return of the spread portfolios which is calculated on a monthly basis using Fama and French portfolios. White standard errors are reported in parentheses. The sample goes from January 1990 to December 2018. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

3.2.2 Dynamic responses of stock returns to policy surprises

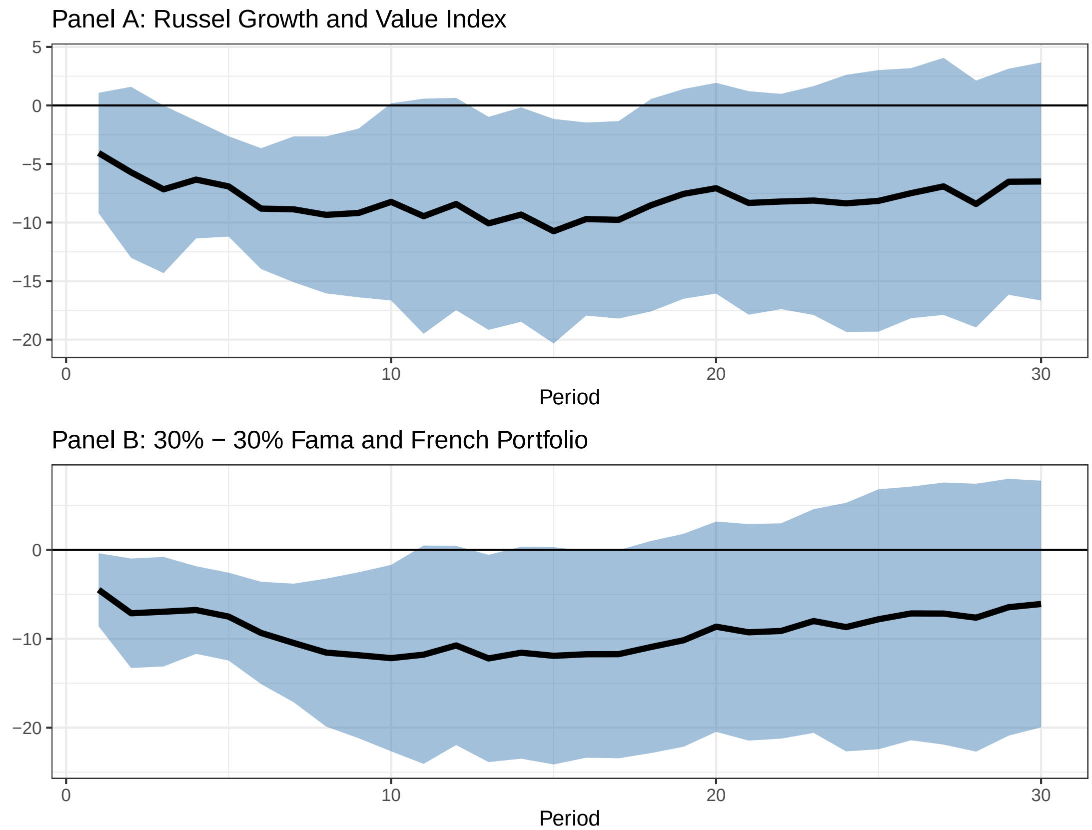
The analysis using a monthly frequency raises the question how long do the different policy responses of stock returns last for. To answer this question I regress the spread returns k-days ahead of the FOMC announcement on the policy surprise:

$$r^s_{t\to k} = \alpha + \beta \times mps_t + \varepsilon_t$$

Figure 6 shows the estimated dynamic response of returns to policy surprises up to 30 days after the FOMC announcement as well as 95% confidence intervals. According to panel A, which uses both Russel Indexes, the spread return does not respond to monetary policy in the day of the announcement. The distinct responses of the Russel Growth and Value Indexes becomes significant only after three days. Yet, the response is persistent and its significance lasts more than two weeks. Even after 30 days the response is negative, although due to a higher noise, it is not statistically significant to 5 % significance level.

The 30% spread portfolio return is from the start on significant and the effects lasts more than 10 days. The difference in response of growth stocks can reach more than 10% in magnitude. Both panels agree upon the fact that the policy response intensifies at the first, reaching its lowest level (around -10%) 5 to 10 days after the policy surprise. This implies that the market reacts with a lag and that investors need time to price the policy surprise.

Figure 3: Dynamic responses of spread portfolios



Panel A plots the reaction of k-days ahead returns from the Russel Growth Index minus the Value Index to monetary policy surprise, where k goes from 1 to 30. Panel B repeats the analysis for the 30% spread portfolio using Fama and French data. 95% confidence intervals are plotted in blue. The sample goes from January 1990 to December 2018.

4 Explaining the monetary policy sensitivity: Duration and financial constraints

The overwhelming evidence of the stronger response of growth stocks to monetary policy raises the question of what economic mechanism explains this response. In this section I attempt to answer this question.

As previously explained two natural candidates are the cash flow duration and the degree of financial constraint of a firm, i.e. a measure of access to external funding. The relation of market to book equity and cash flow duration is straightforward. Growth stocks have dividend payments further in the future, consequently the present value of these dividend payments is more sensitive to movements in discount rates. The magnitude of this sensitivity after a monetary policy shock has not yet been quantified neither there is evidence about its economic significance.

The relation of financial constraints, monetary policy, and market-to-book equity is not as clear-cut. First, Ozdagli (2018) shows that the financial accelerator from Bernanke et al. (1999) implies that constrained firms should be less responsive to monetary policy, since they are less reliant on debt due to a higher external finance premium. Other models, such as models with binding credit constraints like Kiyotaki and Moore (1997), imply that loosening monetary policy might lead the borrowing constraint to unbind, increasing the firms borrowing capacity and investment. In this case, financially constrained firms should respond stronger to monetary policy.

Second, growth and value stocks are characterised by different set of investment opportunities. Growth stocks have better investment opportunities than value stocks, which have more assets in place. As Ehrmann and Fratzscher (2004) put, it is not straightforward to link these variables to the firms' capacity to access external funding.

Although the duration effect and the financial constraint effect explanations are not mutually exclusive explanations, their effect on stock returns are quite different. To formalize this argument consider the present-value identity of a stock price[4]

$$p_t = d_t + log\left(\sum_{n=1}^{\infty} e^{-n(Er_t - Eg_t)}\right) \equiv p\left(Er_t, Eg_t, d_t\right)$$

Where Er_t and Eg_t are the long term average of the discount rates and dividend growths and d_t is the current dividend. Taking the total derivative with respect to a monetary policy shock, ε, yields (I assume that current cash flow d_t is not affected by monetary policy):

$$\frac{dp_t}{d\varepsilon} = \frac{\partial p_t}{\partial Eg_t}\frac{\partial Eg_t}{\partial \varepsilon} + \frac{\partial p_t}{\partial Er_t}\frac{\partial Er_t}{\partial \varepsilon}$$

Now, consider two stocks, called G and V. The difference of monetary policy sensitivity of both stocks is

$$\begin{aligned} \frac{dp_t^G}{d\varepsilon} - \frac{dp_t^V}{d\varepsilon} = &\left(\frac{\partial p_t^G}{\partial Eg_t^G}\frac{\partial Eg_t^G}{\partial \varepsilon} - \frac{\partial p_t^V}{\partial Eg_t^V}\frac{\partial Eg_t^V}{\partial \varepsilon}\right) \\ &+ \left(\frac{\partial p_t^G}{\partial Er_t^G}\frac{\partial Er_t^G}{\partial \varepsilon} - \frac{\partial p_t^V}{\partial Er_t^V}\frac{\partial Er_t^V}{\partial \varepsilon}\right) \end{aligned} \tag{1}$$

Hence, it is possible to decompose the difference in sensitivity of both stocks in cash flow and discount rates effects (Something, which will be useful later). Notice that because

[4] This derivation follows the idea of Chen (2022).

$\frac{\partial p_t}{\partial E g_t} = -\frac{\partial p_t}{\partial E r_t}$, I can re-arrange Equation 1 to get:

$$\frac{dp_t^G}{d\varepsilon} - \frac{dp_t^V}{d\varepsilon} = \left(-\frac{\partial p_t^G}{\partial E r_t^G}\frac{\partial E g_t^G}{\partial \varepsilon} + \frac{\partial p_t^V}{\partial E r_t^V}\frac{\partial E g_t^V}{\partial \varepsilon}\right) + \left(\frac{\partial p_t^G}{\partial E r_t^G}\frac{\partial E r_t^G}{\partial \varepsilon} - \frac{\partial p_t^V}{\partial E r_t^V}\frac{\partial E r_t^V}{\partial \varepsilon}\right)$$

$$\Rightarrow \frac{dp_t^G}{d\varepsilon} - \frac{dp_t^V}{d\varepsilon} = \frac{\partial p_t^G}{\partial E r_t^G}\left(\frac{\partial E r_t^G}{\partial \varepsilon} - \frac{\partial E g_t^V}{\partial \varepsilon}\right) - \frac{\partial p_t^V}{\partial E r_t^V}\left(\frac{\partial E r_t^V}{\partial \varepsilon} - \frac{\partial E g_t^V}{\partial \varepsilon}\right) \tag{2}$$

Equation 2 shows that the spread sensitivity of growth stocks can be driven by the sensitivity of discount rates to monetary policy, $\frac{\partial E r_t}{\partial \varepsilon}$ or the sensitivity of cash flows to monetary policy $\frac{\partial E g_t}{\partial \varepsilon}$. In addition, both effects are magnified by the difference in cash flow duration $\frac{\partial p_t}{\partial E r_t}$.[5]

As the discount rate can be decomposed in risk free rate and risk premium, if the assumption that the risk premium sensitivity to monetary policy is identical for growth and value stocks (This is implied by a one-factor model, for example), the only thing that contributes to the distinct sensitivity of growth and value stocks is the duration, and the sensitivity of the cash flow towards monetary policy, which can be assumed to be captured by financial constraints. Using a Campbell & Shiller decomposition I will show later that this assumption does not hold, i.e. the revisions to risk premium for growth stocks are higher than for value stocks.

4.1 Cash flow duration

To measure cash flow duration I download the firm-level duration measure used in Gonçalves (2021) from Andrei Goncalvez Website and merge it with my firm-level sample. Gonçalves (2021) uses a similar filter as I do, however, he also excludes firms from the utilities and financial industries, causing a significant reduction in my sample to 4,894 firms. I merge the duration data with my sample based on the lagged fiscal year. The duration measure is created using a set of accounting variables to proxy for the future payout of the firms' variables and a VAR to estimate the long-run mean of the accounting variables.

Table 1 shows the summary statistics for duration. The median duration is 48 and so slightly higher than the duration reported by Gonçalves (2021) of 39. To analyse whether duration can explain the responses of growth and value stocks to monetary policy, I conduct

[5]To be more precise, the Maucalay duration is defined as $Dur = -\frac{\partial p_t}{\partial E r_t}$

a similar panel regression analysis as in Table 4 with time and firms fixed effects. As the duration distribution is highly skewed I run the regression using log duration.

Table 9 shows the regression of the daily returns on the duration and monetary policy. Because the present value is more sensitive to discount rate changes the higher the duration, the lower should be the response to monetary policy. This intuition is confirmed by the regression result: Column 1 shows that a higher cash flow duration implies a stronger response of stock returns to monetary policy. A 1% higher duration decreases stock returns by 2.76 percentage points.

Column 2 shows that the effect of market-to-book equity on monetary policy responses vanishes once we control for duration. The duration of the cash flows explains the response of the cross-sectional stock returns which was previously captured by market to book equity. This result confirms cash flow duration as an important variable explaining the effects of monetary policy to stock markets.

Table 9: Panel regressions including duration and financial constraints

	(1)	(2)	(3)	(4)	(5)
log dur	−0.06	−0.04			−0.07
	(0.04)	(0.04)			(0.05)
mb		-0.01^{*}		−0.01	−0.02
		(0.01)		(0.01)	(0.01)
log dur*mps	-2.76^{***}	-2.42^{***}			-4.28^{***}
	(0.77)	(0.67)			(1.23)
FC*log dur					0.02
					(0.04)
mb*mps		−0.26		-0.46^{**}	−0.02
		(0.19)		(0.21)	(0.15)
FC*log dur*mps					2.40^{**}
					(1.01)
FC			0.04	0.03	−0.10
			(0.04)	(0.04)	(0.16)
FC*mps			3.04^{**}	2.67^{**}	-6.90^{**}
			(1.31)	(1.13)	(3.33)
N	274,053	272,144	312,884	306,091	231,003
R^2	0.63	0.63	0.37	0.37	0.67

The table estimates the regression of returns on market to book equity, monetary policy, cash flow duration, and financial constraints. The observations go from January 1990 to December 2018. mps stands for monetary policy surprise, mb for market-to-book equity and log dur for the log of duration. FC is a dummy variable, which takes the value of 1, if the financial constraint index is larger than the median. All regressions use time and firms fixed effects. Two-way clustered standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

4.2 Financial constraints

Next, I attempt to understand how financial constraints relate to the responses of growth and value stocks to monetary policy. Several studies have proposed different measures of financial constraint. Here, I follow Gürkaynak et al. (2022) and use the measure of Schauer et al. (2019), who uses a weighted average of size, interest coverage, return on assets, and cash holdings to construct a financial constraint index on firm-level. This measure has been shown to outperform other financial constraint measures (see Schauer et al. (2019) for details).

After constructing the financial constraint index, I average it over the previous four quarters to create a yearly measure. Finally, as proposed by Schauer et al. (2019) I use the financial constraint index to construct two groups of constrained and unconstrained firms. Specifically, a create a dummy variable, FC, which takes the value of 1 if the firm's value of the financial constraint index is larger than the sample median, and 0 otherwise. Table 2 shows that FC has a correlation with market to book equity of -20% implying that, at least for this measure of financial constraint, value stocks are more financially constrained.

Column 3 of Table 9 shows that financial constraints have a positive and significant effect on the sensitivity of stock returns to monetary policy. Financially constrained firms respond, ceteris paribus, 3 percentage points more, to monetary policy. Column 4 runs the same regressions but includes market to book equity. It shows that, after controlling for the effects of financial constraints, market to book equity is still significantly different from 0 and its magnitude remains unchanged to the results presented in Table 3. This result confirms that, even though financial constraints, do explain heterogeneous responses of the cross-section of stock returns, they do not explain the response of growth and value stocks.

Equation 2 implies that the duration effect complements the effects of financial constraints. Hence, the equation motivates a triple interaction factor of financial constraints, duration, and monetary policy. Column 5 shows the results of this regression. The coefficient of the triple interaction is positive and significantly different from zero. Hence, when accounting for the interaction effect of duration, financial constraints do have explanation power over growth and value stocks.

5 Policy surprises and stock price decomposition

This section conducts a Campbell & Shiller decomposition to separate the return responses to monetary policy in risk premium, risk-free rate, and cash flow effects. As I previously showed the cash flow duration can account for a good portion of the variation in response of growth and value stocks. Yet, there could be effects coming from these three components that could be reinforcing or counteracting the duration effect. This section attempts to address these.

The log-linearization implies that the duration is pinned down by the steady state log dividend yield, $\bar{dp}$ (specifically, $Dur = 1 + e^{-\bar{dp}}$). Because it is common to assume that ρ is equal through the different decompositions, the duration effect will be "assumed away" in this section. This is an advantage, because the Campbell & Shiller decomposition will capture the effects on discount rates and cash flow without the duration effect.

To ensure robustness of the results, I proceed with the decomposition analysis on the Russel Indexes and Fama and French portfolios. Due to the limitations of the decomposition to monthly data, I abdicate of a firm-level analysis because of the significant amount of noise.

5.1 Decomposing stock returns

Following the log-linearization of Campbell and Shiller (1988) current stock price movements can be explained by revisions on future expected dividends, expected excess returns or real rates. Formally, the unexpected component of stock returns is given by following identity:

$$e^y_{t+1} = \tilde{e}^d_{t+1} - \tilde{e}^r_{t+1} - \tilde{e}^y_{t+1} \tag{3}$$

where

$$\begin{aligned}
e^y_{t+1} &= (E_{t+1} - E_t)y_{t+1} \\
\tilde{e}^d_{t+1} &= (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} \\
\tilde{e}^r_{t+1} &= (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j r_{t+1+j} \\
\tilde{e}^y_{t+1} &= (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j y_{t+1+j}
\end{aligned}$$

d is the log-dividend, r the real rate and y the excess return. The log-linearization introduces ρ, which is the steady-state ratio of the equity price to the price plus dividend. Following Campbell and Ammer (1993) I set it to 0.9962.

Given identity 3 the variance decomposition of unexpected equity returns can be determined:

$$\begin{aligned}
&Var(e^y_{t+1}) = Var(\tilde{e}^d_{t+1}) + Var(\tilde{e}^r_{t+1}) + Var(\tilde{e}^y_{t+1}) \\
&- 2Cov(\tilde{e}^d_{t+1}, \tilde{e}^r_{t+1}) - 2Cov(\tilde{e}^d_{t+1}, \tilde{e}^y_{t+1}) + 2Cov(\tilde{e}^r_{t+1}, \tilde{e}^y_{t+1})
\end{aligned} \tag{4}$$

The work of Campbell and Ammer (1993) provides a VAR specification to estimate these future expectations. Let z_t be a vector of state variables, which include the expected returns and the real rates. Then:

$$z_{t+1} = Az_t + \varepsilon_{t+1} \tag{5}$$

Equation 5 enables to back up the news on expected excess returns, real rates, and current expected returns:

$$
\begin{aligned}
e^y_{t+1} &= s_y \varepsilon_{t+1} \\
\tilde{e}^y_{t+1} &= s_y \rho A (1-\rho A)^{-1} \varepsilon_{t+1} \\
\tilde{e}^r_{t+1} &= s_r (1-\rho A)^{-1} \varepsilon_{t+1}
\end{aligned}
$$

where s_y and s_r are selection matrices for y and r, respectively.

The news on future dividends are estimated as residuals of the identity:

$$
\tilde{e}^d_{t+1} = e^y_{t+1} + \tilde{e}^y_{t+1} + \tilde{e}^r_{t+1}
$$

Following the studies of Campbell and Ammer (1993), Bernanke and Kuttner (2005) and Maio (2014) I use a six variable state vector which include the excess equity return, the real interest rate (1-month treasury bill adjusted by the CPI), the relative bill rate (the 3-month treasury bill minus its 12-month lagged moving average), the change in the 3-month treasury bill, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields.

Table 10 shows the variance decomposition of excess returns (calculated with equation 4). As the price-dividend ratios of the Russel Index go back only to 1995, I extrapolate the data using the fitted value of a regression of the price-dividend ratio of the S&P500 on the price-dividend ratio of both Russel indexes. In this way the sample starts in 1979. As previously documented, the variance of S&P500 returns is mainly explained by the variance of cash-flow news, future excess returns news and their covariance. The variance of future dividends has the largest share.

When comparing the Russel Value and Growth Index two features stand out: First, the variance of future returns for the Russel Growth Index is much higher than for the Russel Value Index (Future returns of growth stocks vary almost as much as the unexpected excess returns). Second, the covariance of dividends and future excess returns is much higher in magnitude, but it is also positive. Although the variance of dividends makes up around 55% for both indexes, future excess returns make up almost 90% in the growth index. This is offset by the large positive covariance between dividends and future returns.

An important caveat, pointed out by Bernanke and Kuttner (2005), is that the decomposition will attribute too much weight to dividends, in case the VAR understates the predictability of expected returns. The low adjusted R squared shows that this understatement might exist. The price-dividend ratio is a significant predictor of future returns for the Russel Growth Index, but not for the Russel Value Index and the S&P 500 (see Table C.3

in appendix). This might be the reason why the variance of future returns of value stocks are considerably lower than for growth stocks.

Table 10: Variance decomposition of excess equity returns

	S&P500		Russel Value		Russel Growth	
	Total	Share (%)	Total	Share (%)	Total	Share (%)
var(excess return)	18.50		17.46		23.78	
var(dividends)	7.36	39.76	9.69	55.50*	13.54	56.95**
		(25.62)		(31.72)		(25.84)
var(future returns)	2.78	15.01	2.42	13.86	20.93	88.01
		(22.36)		(17.46)		(90.18)
var(real rates)	0.87	4.72*	0.97	5.57*	0.78	3.27**
		(2.73)		(3.31)		(1.58)
- 2 cov(div, future excess return)	4.99	26.97	2.29	13.13	-12.79	-53.80
		(17.35)		(33.12)		(118.39)
- 2 cov(div, real rate)	1.94	10.51	2.08	11.91	-0.93	-3.91
		(13.52)		(17.41)		(8.31)
2 cov(future excess return, real rate)	0.56	3.02	0.00	0.03	2.25	9.47
		(7.96)		(12.65)		(17.81)
$\bar{R}^2$ from excess return equation		-0.01		-0.00		0.01

The table shows the decomposition of the variance of current unexpected excess returns into the variances of unexpected future dividends, real interest rates, future excess returns, as well as the covariances among them. The results are constructed using a first-order VAR, which includes the excess equity return, the real interest rate, the relative bill rate, the change in the 3-month bill rate, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields. The sample period goes from Jan-1978 to Dec-2018. Standard errors are calculated using the delta method and are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

5.2 Effects of monetary policy on aggregated news

Bernanke and Kuttner (2005) extend Campbell and Ammer (1993)'s approach to account for the effects of monetary policy surprises on the news components. Specifically, they include monetary policy surprises in the VAR:

$$z_{t+1} = Az_t + \Phi mps_{t+1} + \nu_{t+1} \tag{6}$$

Since monetary policy surprises and the lagged state variables are orthogonal, Bernanke and Kuttner (2005) estimate the regression above using a two-step estimation method. First, the dynamics of the first-order VAR are estimated without the policy surprise. In the second step, the residuals are regressed on the monetary policy surprises. This method allows to use a larger sample to estimate the matrix A and thus obtain more precise estimates. The effects of monetary policy surprises are given as follows:

$$
\begin{aligned}
\eta_y &= s_y \Phi \\
\eta_r &= s_r (1 - \rho A)^{-1} \Phi \\
\eta_{\tilde{y}} &= s_y \rho A (1 - \rho A)^{-1} \Phi \\
\eta_d &= (s_y + s_r)(1 - \rho A)^{-1} \Phi
\end{aligned}
$$

Since the VAR specification requires a steady frequency, the model is estimated in a monthly frequency. Table 11 shows the estimated responses of the S&P500, Russel Value Index and Growth Index. The results for the S&P500 favour cash flows news as the main component affected by monetary policy, i.e., price movements in the stock market caused by monetary policy arise mainly, because investors revise their expectation of future cash flows. This outcome resembles the results of Bernanke and Kuttner (2005), even though their policy surprise is different. Table 11 also shows that transmissions of monetary policy to value and growth stocks differ considerably. Monetary policy affects prices of growth stock mainly through revisions of future excess returns whereas they affect value stocks (similarly to the aggregate market) through revisions of future dividends. The economic reason why revisions of the risk premium for growth stocks are larger than for value stocks is not clear. Revisions to expected real rates are flat as expected, since duration is equal in both cases, for the Russel Value Index and Growth Index.

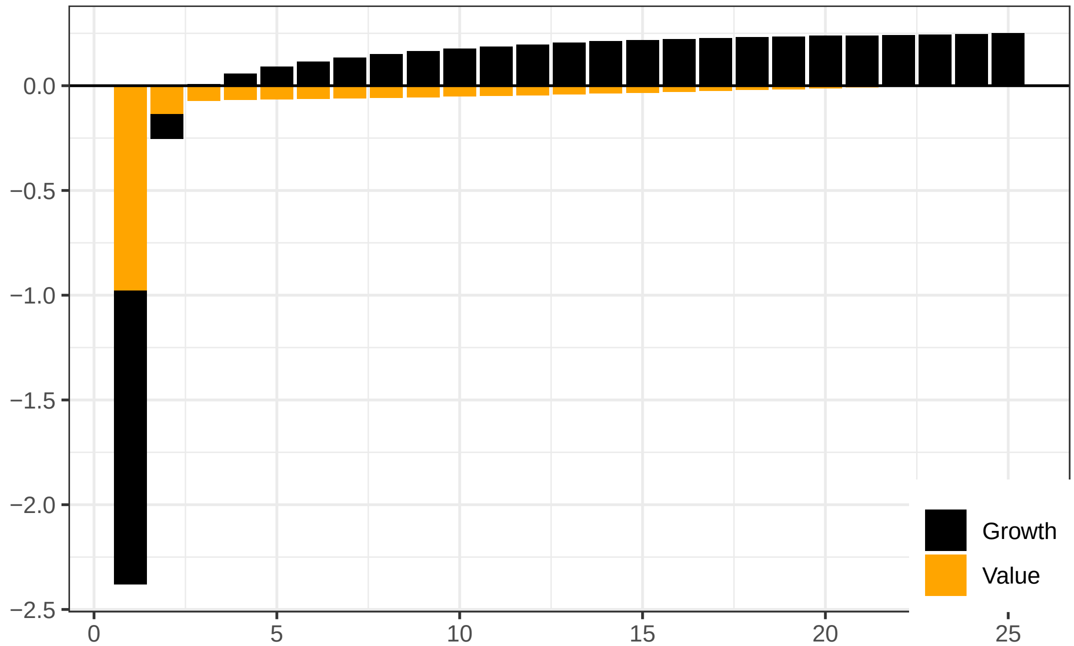
Table 11: Breakdown of monetary policy effects on unexpected excess returns

	S&P500	Russel Value	Russel Growth
Current excess return	-16.86***	-14.08***	-21.34***
	(5.34)	(5.34)	(6.18)
Future excess returns	1.38	1.70	18.74***
	(2.99)	(2.95)	(6.29)
Real interest rate	2.77**	3.55***	2.83**
	(1.26)	(1.35)	(1.21)
Dividends	-12.71***	-8.83**	0.23
	(3.64)	(4.31)	(5.25)

The table estimates the impact of monetary policy surprises on the current unexpected excess return and its different components. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative bill rate, the change in the 3-month bill rate, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields. The VAR is estimated from Jan-1979 to Dec-2018. The monetary policy surprises are monthly aggregated and go from the Jan-1990 to Dec-2018. Coefficients are estimated in two-steps. Standard errors are calculated using bootstrapping and are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

To gain a better understanding of why revisions of future discount rates are stronger for growth stocks, Figure 11 plots the impulse response of the excess return regression. The figure helps to see the difference in the long-run forecastability in excess returns. The reaction of value excess returns is minor after one year (and negative) whereas the response of growth stocks is positive and relatively big even after 25 months. Discounting these responses to the present and summing them up yields a big positive reaction of future discount rates.

Figure 4: Impulse response of excess returns

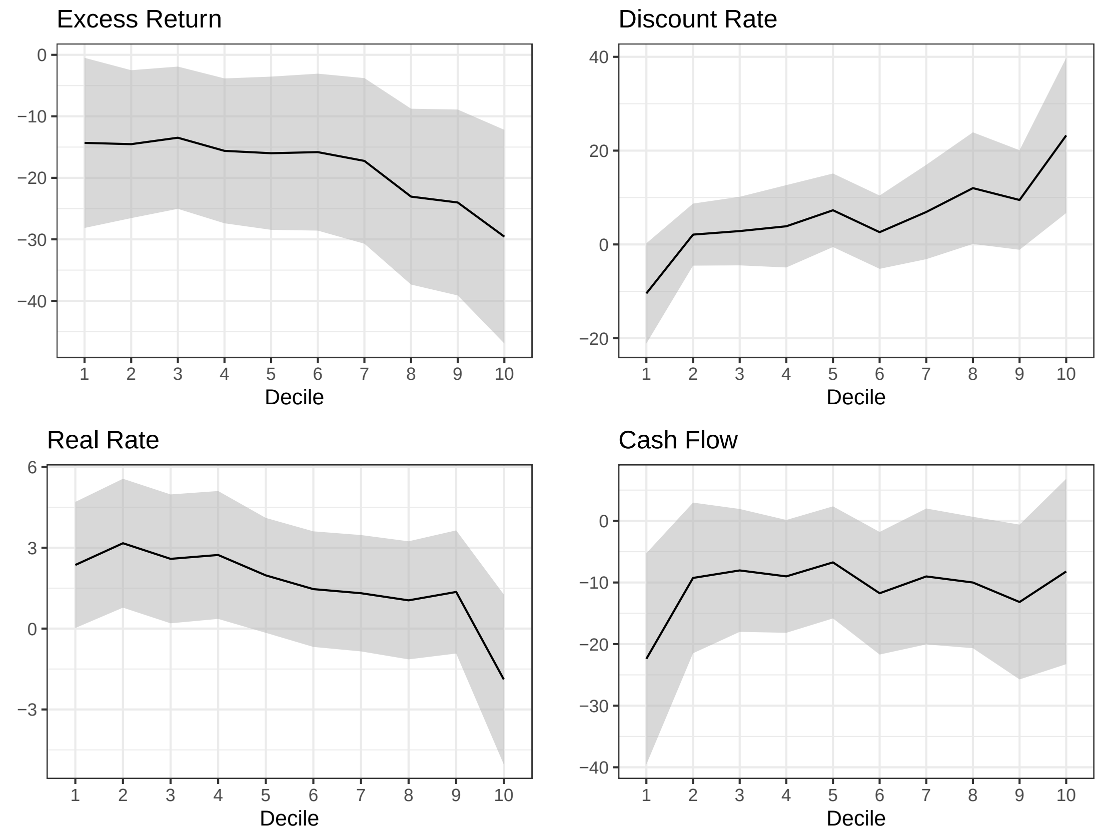


The figure shows the impulse responses of the excess returns from Russel growth and value stocks after a monetary policy surprise up to 25 periods ahead. The contemporaneous effect is omitted for illustrative purposes. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative bill rate, the change in the 3-month bill rate, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields. The VAR is estimated from Jan-1979 to Dec-2018. The monetary policy surprises are monthly aggregated and go from the Jan-1990 to Dec-2018. Coefficients are estimated in two-steps.

5.3 Decomposition of Fama and French portfolios

In this section I repeat the Campbell-Shiller decomposition for Fama and French portfolios sorted by market-to-book equity. The goal is to investigate the effects of policy surprises on a lower level of aggregation. Figure 5 plots the responses of the unexpected excess returns and from its three components against the ten deciles.

Figure 5: Response of unexpected excess returns to policy surprises using Fama and French



The figure shows the reaction of the single components of the unexpected excess returns of Fama and French portfolios. The portfolios are sorted from low to high market-to-book equity. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative bill rate, the change in the 3-month bill rate, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields. The VAR is estimated from Jan-1979 to Dec-2018. The monetary policy surprises are monthly aggregated and go from the Jan-1990 to Dec-2018. Coefficients are estimated in two-steps. Standard errors are calculated using bootstrapping. 95% confidence intervals are drawn around the point estimation.

The upper left figure shows that the response of the forecasting errors to monetary policy decreases with market-to-book equity, i.e., the revision of stock prices with relatively high market-to-book equity is larger. The magnitude of the response doubles from the first to the last decile. The discount rate news is typically positive and increases on the deciles, implying that the impact of monetary policy on revisions of discount rates are stronger growth stocks. The revisions of future real rates are, with exception of the last decile, positive and do not vary significantly. It is noteworthy that the portfolio deciles indicate different insights regarding the revisions of future cash flows. Given the outcome in Table 11 an increasing pattern of the impacts on cash flow news would be expected. Indeed, the cash flow revisions for the first portfolio is notably larger in magnitude, but this pattern does not continue for the other portfolios. Generally, Figure 5 confirms the higher sensitivity of discount rates news for growth stocks from the previous analysis, but not of the cash flow news for value stocks.

6 Theoretical framework

In this section I show how to reconcile my results of value and growth stocks with a theoretical model. To do so, I use the model from Lettau and Wachter (2011), which is the baseline asset pricing model on the behaviour of growth and value stocks. In this model firms differ solely by the cash flow duration. This mechanism and the fact that only dividend shocks are priced enables the model to match the value premium seen in the data.

Is is important to notice that, although my empirical results show indeed that there are probably other sources of heterogeneity in the responses of growth and value stocks to monetary policy, these results are harder to motivated by economic theory and might over complicate the model dynamics. I leave the construction of a structural and more complex model for future research.

I model the dynamics of four different variables: Aggregate dividend growth, expected dividend growth, risk-free rate, and price of risk.

$$\begin{aligned}
\Delta d_{t+1} &= z_t + u^d_{t+1} \\
z_{t+1} &= (1-\phi_z)g + \phi_z z_t + u^z_{t+1} \\
r^f_{t+1} &= (1-\phi_r)\bar{r}^f + \phi_r r^f_t + u^{rf}_t \\
x_{t+1} &= (1-\phi_x)\bar{x} + \phi_x x_t + u^x_{t+1}
\end{aligned} \tag{7}$$

u_t are iid normal reduced-form shocks with mean 0 and standard deviation σ.

Following Lettau and Wachter (2011) I assume that only fundamental dividend risk is priced. The stochastic discount factor is given by

$$M_{t+1} = \exp\left(-r^f_{t+1} - \frac{1}{2}\sigma_d^2 x_t^2 - x_t\sigma_d\epsilon_{t+1}\right)$$

Let $P^{(n)}_t$ denote the time-t price of the asset that pays the aggregate dividend at time $t+n$ (from here on referred to as zero-coupon equity). Then, the price-dividend ratio of a zero-coupon equity is affine on the state variables (see Lettau and Wachter (2011) for the complete derivation):

$$\frac{P_t^{(n)}}{D_t} = \exp\left(A^{(n)} + B_z^{(n)}(z_t - g) + B_r^{(n)}(r_{t+1}^f - \bar{r}^f) + B_x^{(n)}(x_t - \bar{x})\right) \tag{8}$$

with coefficients

$$B_z^{(n)} = \frac{1-\phi_z^n}{1-\phi_z} \qquad\qquad B_r^{(n)} = -\frac{1-\phi_r^n}{1-\phi_r}$$

and

$$B_x^{(n)} = B_x^{(n-1)}\left(\phi_x - \sigma_{dx}\right) - \sigma_d^2 - B_z^{(n-1)}\sigma_{dz} - B_r^{(n-1)}\sigma_{dr}$$

with boundary condition $B_x^{(0)} = 0$. The aggregate market portfolio is the claim to all future dividends. Therefore, under certain parametric conditions the price dividend ratio of the market is

$$\frac{P_t}{D_t} = \sum_{n=1}^{\infty} \frac{P_t^{(n)}}{D_t} = \sum_{n=1}^{\infty} \exp\left(A^{(n)} + B_z^{(n)}(z_t - g) + B_r^{(n)}(r_{t+1}^f - \bar{r}^f) + B_x^{(n)}(x_t - \bar{x})\right) \tag{9}$$

Note that the price–dividend ratio is not an affine function of the state variables. Lettau and Wachter (2011) calculate the aggregate return by first aggregating the price-dividend ratio. I instead opt to first derive a close form solution for the returns on the zero-coupon equity and then aggregate to the market. The reason is that I am interested in understanding how the effects of monetary policy on returns depend on the dividend payment of the assets.

Taking the log of Equation 8 and subtracting the price one-period forward by the price from today yields:

$$\begin{aligned} r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} = A^{(n-1)} - A^{(n)} + [B_z^{(n-1)}(z_{t+1} - g) - B_z^{(n)}(z_t - g)] + \\ [B_r^{(n-1)}(r_{t+2}^f - \bar{r}^f) - B_r^{(n)}(r_{t+1}^f - \bar{r}^f)] + [B_x^{(n-1)}(x_{t+1} - \bar{x}) - B_x^{(n)}(x_t - \bar{x})] + \Delta d_{t+1} \end{aligned}$$

Next, I subtract the one-period expected return from realized returns. The only remaining components is the reduced-form shock.

$$r_{t+1}^{(n)} - E_t\left(r_{t+1}^{(n)}\right) = \left(B_z^{(n-1)}u_{t+1}^z + B_r^{(n-1)}u_{t+1}^{rf} + B_x^{(n-1)}u_{t+1}^x + u_{t+1}^d\right) \tag{10}$$

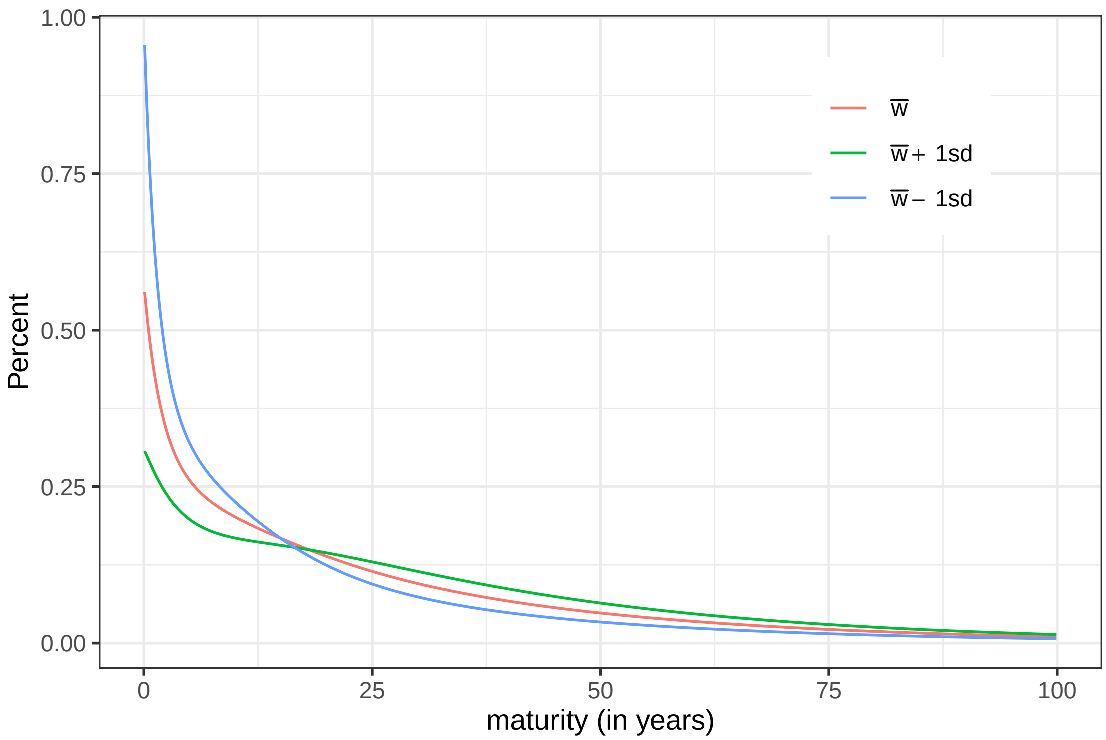
Knox and Vissing-Jorgensen (2022) show that the one-period return on the market can be expressed as the value-weighted average of the one-period returns. Hence, I can aggregate the zero-coupon equity returns to get the market return as a function of the state variables.

$$r_{t+1} - E_t\left(r_{t+1}\right) = \sum_{n=1}^{\infty} w_t^{(n)} \left(B_z^{(n-1)} u_{t+1}^{z} + B_r^{(n-1)} u_{t+1}^{rf} + B_x^{(n-1)} u_{t+1}^{x} + u_{t+1}^{d} \right) \tag{11}$$

where $w_t^{(n)} = \frac{P_t^{(n)}}{P_t}$.

The weights, $w_t^{(n)}$, are non-linear functions of the state variables. To facilitate the calculation, I assume that the state variables are equal to their unconditional mean when calculating the weights. To analyse the importance of this assumption, Figure 6 plots the weights, for the case when the state variables are equal to their unconditional mean and for the case when they are 1 standard deviation away from the mean. The weight difference converges to zero and is very similar after 20 years. Generally, the weights are not very sensitive to the state variables.[6]

Figure 6: Zero-coupon equity weights



The figure shows the weights in percent defined as the price of a zero-coupon equity relative to the price of the market portfolio for each maturity up to 750 quarters.

The parameters are calibrated in a monthly basis. The persistence parameters, the unconditional mean and volatility in Equation 7 are taken from Lettau and Wachter (2011) and the frequency is adjusted accordingly. Table 12 shows the calibrated parameters.

[6]As a robustness check I simulated 100,000 weights distributions. The median and the 95% confidence intervals are similar to Figure 6.

Table 12: Summary of calibration

Parameter	Value	Description
ϕ_r	0.99	Persistence risk-free rate
ϕ_d	0.98	Persistence exp. div growth
ϕ_x	0.97	Persistence price of risk
$\bar{r}^f$	8 bp	mean of risk-free rate
g	10.75 bp	mean of exp. div growth
$\bar{x}$	29.44	mean of x_t/σ^d
σ_d	2.89%	std. deviation of div. growth
σ_{r^f}	0.07%	std. deviation of risk-free rate
σ_z	0.09%	std. deviation of exp. div. growth
σ_x	4	std. deviation of x_t/σ^d
ρ_{dz}	-0.83	corr. of div growth and its expectation
ρ_{dr}	-0.3	corr. of divi growth and risk-free rate
ρ_{zx}	0.35	corr. of exp. div growth and price of risk
$\rho_{dx}, \rho_{zr}, \rho_{xr}$	0	further correlations

The table shows the parameter calibration according to Lettau and Wachter (2011) and adjusted to monthly frequency.

6.1 Identification of monetary policy

To reconcile the model with the empirical evidence, an assumption about how monetary policy interacts with the returns has to be made. The shock, u_t^i, is a reduced-form shock, i.e. a combination of structural shocks. Hence, I assume that around FOMC announcements, the reduced-form shock is mainly driven by a monetary policy shock, i.e. $u_t^i = a^i \varepsilon_t^{MP}$, where $i = d, z, r^f, x$. Furthermore, I assume that monetary policy does not affect dividend payment contemporaneously, i.e. $a^d = 0$.

Given these assumptions Equation 11 reduces to

$$r_{t+1} - E_t\left(r_{t+1}\right) = \sum_{n=1}^{\infty} w_t^{(n)} \left(a_z B_z^{(n-1)} + a_r B_r^{(n-1)} + a_x B_x^{(n-1)}\right) \varepsilon_{t+1}^{MP} \tag{12}$$

The model predicts that monetary policy shocks affect the return of a zero-coupon equity either through effects on the real rate, expected dividend growth, or price of risk. The effects on the term structure of equity are determined by the loadings B.

To identify a_r, a_z, and a_x, I use Equation 12 to calibrate the three parameter using the responses of the S&P 500 decomposition. Recall that the effect of monetary policy surprise on each component of the S&P 500 is -12.7, 2.8, and 1.4 for dividends, real rates and risk premium, respectively. Hence, I can match the three components of the model to these results. The a's are implied by following equations:

$$\sum_{n=1}^{\infty} w_t^{(n)} B_z^{(n-1)} a_z = -12.7$$
$$\sum_{n=1}^{\infty} w_t^{(n)} B_r^{(n-1)} a_r = -2.8$$
$$\sum_{n=1}^{\infty} w_t^{(n)} B_x^{(n-1)} a_x = -1.4$$

Solving for the a's yields:

$$a_z = \frac{-12.7}{\sum_{n=1}^{\infty} w_t^{(n)} B_z^{(n-1)}} \tag{13}$$
$$a_r = \frac{-2.8}{\sum_{n=1}^{\infty} w_t^{(n)} B_r^{(n-1)}} \tag{14}$$
$$a_x = \frac{-1.4}{\sum_{n=1}^{\infty} w_t^{(n)} B_x^{(n-1)}} \tag{15}$$

Table 13 Panel A shows the estimates for the one-period monetary policy effects on the state variables. I calculate w_t^n in three different cases: When the state variables are equal to their unconditional mean and for the case when they are one standard deviation higher or lower than the unconditional mean.

Overall a tightening monetary policy shock increases the risk-free rate, and price of risk, and decreases dividend growth expectations, which is in line with the duration and cash-flow effects of monetary policy. Furthermore, the estimates are not very sensitive to changes in the state variables. The fact that the coefficients are so different in magnitude deserves some attention. First, notice that they are all in percent. For example, a positive monetary policy surprise increases the 1-month real rate by 3 basis points. Although this number sounds low, recall from Table 12 that the standard deviation of the real rate is 7 bp and the unconditional mean 8 bp. Table 13 Panel B shows the response of each state variable relative to its mean and standard deviation. It shows that while real rates and price of risk move about 3 to 5 % of its standard deviation, dividend growth reacts with movements about one third times its standard deviation. Hence, it implies that dividend growth is substantially more sensitive to monetary policy.

Table 13: Effects of monetary policy surprises on stock returns

Panel A:	Estimated response of response		
	a_r	a_z	a_x
mean	0.03	-0.29	106.89
+ 1sd	0.03	-0.31	114.49
- 1sd	0.03	-0.27	100.56
Panel B:	**Relative response of state variables**		
Mean	36.5%	-265.3%	3.6%
Std dev.	4.7%	-36.27%	3.1%
Panel C:	**Response to monetary policy**		
	Value	Market	Growth
Data	-14.08%	-16.86%	-21.34%
Model	-13.53%	-16.86%	-20.18%

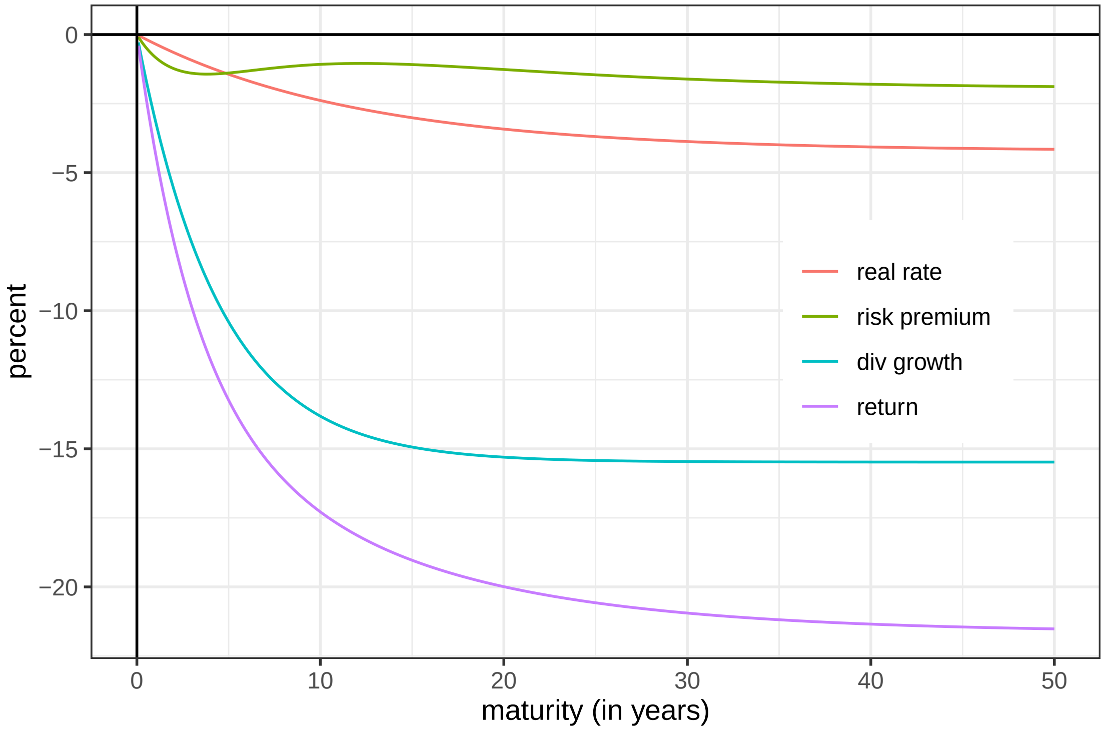
Panel A shows the estimated effects of monetary policy surprises on stock returns on each of the state variables. Panel B shows the estimated effects of monetary policy surprises on stock returns on each of the state variables relative to their unconditional mean and standard deviation. Panel C illustrates the response of value and growth stocks to monetary policy from the model and the data.

I first investigate how the term structure of equity reacts to monetary policy. Figure 7 shows the response of the term structure of equity and its components to monetary policy implied by the model. Overall, the zero coupon equity returns are mainly driven by revisions on cash flows. Because dividend growth is expected to increase over time, the further the dividend payment in the future, the higher will be its revisions to monetary policy. Risk premium and real rate are very small, implying that the duration effect is minor in comparison to the cash flow effect. Hence, the model implies that growth stocks are more sensitive to monetary policy, since their expected cash flows are larger. This result contradicts the literature that argues that the duration effect is the main driver of monetary policy.

6.2 Growth and value stocks

To construct the growth and value stocks, Lettau and Wachter (2011) assume a deterministic shares process, which is added to the model after simulating the zero-coupon equities. For the sake of this paper, I construct the returns of growth and value stocks by changing the weights $w_t^{(n)}$, which is a simpler approach and does not require simulation. A value-weighted portfolio of zero-coupon equity is the market portfolio. However, slightly increasing the weights on securities that pay dividend relative early yields value portfolios, whereas doing the opposite results in growth portfolios.

Figure 7: Zero-coupon equity returns decomposition

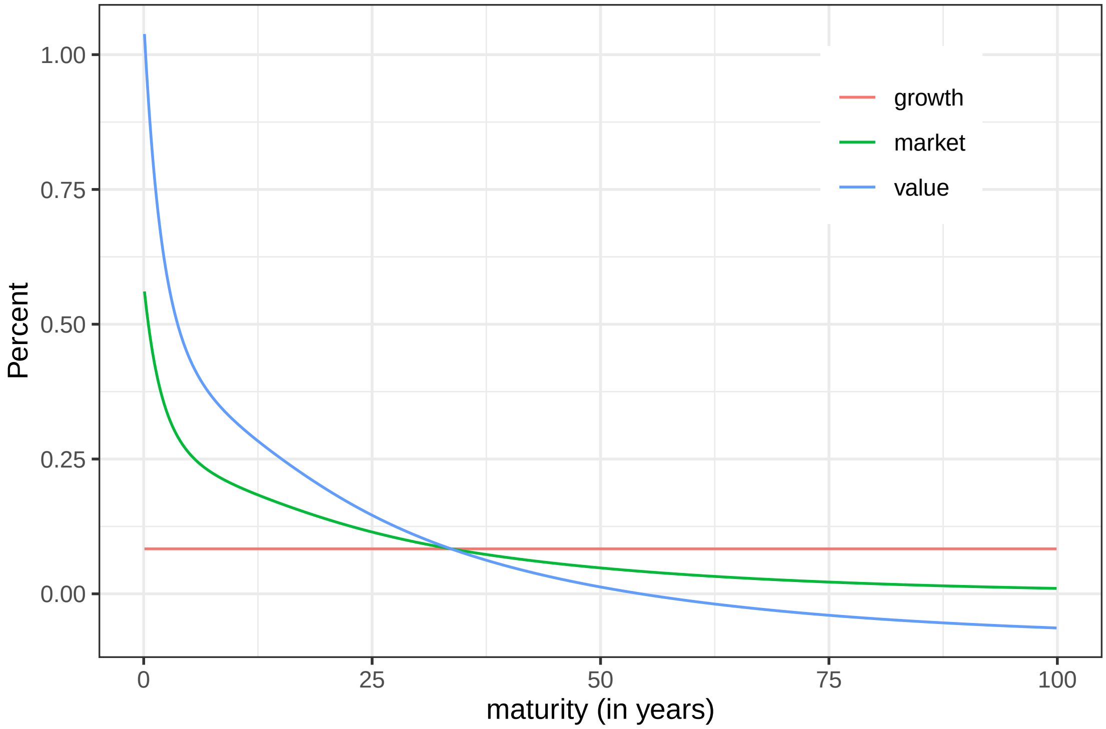


The figure shows the response of the zero-coupon equity returns to monetary policy in percent. The response is decomposed in effects of real rates, risk premium, and dividend growth revisions.

I construct a growth index by assuming equal-weights. To construct the value index, I take the difference between weights of the market portfolio and the growth portfolios and sum it to the market portfolio. Figure 8 show the weights of the growth and value indexes by maturity. The growth portfolio weights all zero-coupon equity identically. Thus, it has, relative to the market, a higher weight on stocks with higher duration. The value index, on the other hand, has relatively high weights on short-maturity equities.

Table 13 Panel C shows the reactions of the market, as well as the growth, and the value portfolios to monetary policy. The market reaction to monetary policy is equal to the empirical results by construction and is shown only for comparison with the growth and value portfolio. In line with the data, the model implies that growth stocks respond more to monetary policy and the spread return is about 6 percentage points. The model matches the responses of the Russel Growth and Value indexes well, which might imply that the zero coupon equity weights from the Russel 1000 might be similar to the ones assumed here.

Figure 8: Zero-coupon equity weights for growth and value portfolios



The figure shows the distribution of weights of the growth and value portfolios relative to the market portfolio.

7 Conclusion

This paper provides substantial new evidence of monetary policy channels to stock returns. Firms with higher valuation, in form of market-to-book equity, experience a relatively greater drop in stock prices following a tightening surprise. This result is consistent across different levels of aggregation and is thus not susceptible to diversification or idiosyncratic noise. I also explain why my findings contradict those of Maio (2014), who found the opposite effect. To identify the causal effect of monetary policy on stock returns, it is crucial to use an exogenous policy surprise. In addition, lower frequency data may increase the noise and make it difficult to identify any effect. An investigation of the dynamic responses reveals that the stronger response of growth stocks compared to value stocks is persistent and can endure for over two weeks. The magnitude of the stronger response can reach up to 10% even after several days.

It is well-known that growth stocks are higher duration assets, yet it is still unclear whether this is the determining factor for the stronger response of growth stocks to monetary policy. To shed light on this question, I show through a firm-level panel regression that cash flow duration indeed explains the sensitivity of growth relative to value stocks. I also provide evidence, that financial constraints explain a significant portion of cross-sectional stock returns responses to monetary policy, but they are not related to market-to-book equity and monetary policy jointly.

A Campbell-Shiller decomposition demonstrates that growth stocks react more, because investors revise their expected future risk premium more strongly for growth stock than for value stocks following a monetary policy surprise. This effect complements the duration effect, as growth and value stock have the same duration in the Campbell & Shiller by construction. I leave for future research to understand the economic reasons why revisions in discount rates are stronger for growth stocks. Finally, I build upon the model of Lettau and Wachter (2011) and show how my empirical results on the duration effect can be reconciled in an asset pricing model. The model matches the sensitivity of responses of growth and value stocks found in the data. This speaks in favour of duration being indeed the main driver of the different sensitivities.

Appendix

A Derivation of monetary policy surprises

This exposition closely follows Gürkaynak et al. (2005) Appendix. The Federal funds future contracts have a settlement price which is based on the average federal funds rate over the month specified in the contract.[7]. Let i_0 be the average federal funds rate prevailing before the fed's decision at time $t-\Delta t$ and i_1 the rate after the decision at time t. Finally, denote d as the day of the month of the announcement and D the total number of days in the month. Then, the implied spot rate before the FOMC meeting is

$$ff^1_{t-\Delta t} = \frac{d}{D} i_0 + \frac{D-d}{D} E_{t-\Delta t}(i_1) + \mu^1_{t-\Delta t} \tag{A.1}$$

Where μ^1 is the risk premium. Leading this equation to after the meeting yields:

$$ff^1_t = \frac{d}{D} i_0 + \frac{D-d}{D} i_1 + \mu^1_t \tag{A.2}$$

Kuttner (2001) calculates the surprises by subtracting the spot rate after from the spot rate before the meeting:

$$mp1_t \equiv i_1 - E_{t-\Delta t}(i_1) \approx [ff^1_t - ff^1_{t-\Delta t}] \frac{D}{D-d} \tag{A.3}$$

Two remarks are important here: First, the equation holds only if changes in risk premium μ in this window is small in comparison to the change in expectations itself. An assumption which is backed empirically by Piazzesi and Swanson (2008). Second, the scale $(D-d)/D$ can lead to measurement errors if the FOMC meetings occur very late in the month. Because of that, the unscaled change in the next-month federal funds futures contract is used in the announcements that takes place in the last seven days of the month.

Gürkaynak et al. (2005) extend this analysis to extract two monetary policy surprise factors. They argue that two latent factors can better describe asset prices movements. The Kuttner shock captures current policy surprises, but not changes in the future expectation of these surprises, something which affects asset prices as well. To enhance the analysis, they consider next to the current month federal funds rates future contracts, the three-months funds future contract, and the prices of eurodollars future contracts with maturity 1.5, 2.5 and 3.5 quarters to expiration on average. Formally, let X be a vector of the standardized changes in the future prices. I can decompose X in five principal components F with loadings in Λ.

$$X = F\Lambda \tag{A.4}$$

Nakamura and Steinsson (2018) take the first factor with the largest R2, call it $F1$ and rescale it so it has a one unit impact on the one year treasury yield change. Let Δy^1 denote

[7] More precisely, the value at expiration is 100 minus the average federal funds rate.

the daily change in the one year treasury yield. I run the regression:

$$\Delta y^1 = \rho F1 + \epsilon \tag{A.5}$$

In which case the NS surprise is:

$$mps = F1 \cdot \rho \tag{A.6}$$

B Fixed Effects Specification

B.1 Omitted variable bias

I first consider the case when there is an omitted variable bias which is time but not firm dependent. This variable could be, for example, business or credit cycles. especially the latter increases the valuations in the markets and thus might be correlated with market-to-book values and stock returns.

Consider following population model for a given firm i and announcement dates $t = 1, 2, .., T$:

$$r_{t,i} = \beta_0 + \beta_1 \times mp_t + \beta_2 \times mb_{i,t} + \beta_3 \times mp_t \times mb_{i,t} + \gamma_0 \times c_t + \gamma_1 \times c_t \times mp_t + \varepsilon_{i,t} \tag{B.1}$$

where r denotes returns, mp monetary policy surprises and mb market-to-book ratio. Also, c is an unobserved effect which is firm invariant.

Since $mb_{i,t}$ and c_t are potentially correlated, I can write c as a linear projection of mb:

$$c_t = \delta_0 + \delta_1 \times mb_{i,t} + \nu_t \tag{B.2}$$

Plugging it back in B.1 yields:

$$r_{i,t} = (\beta_0 + \gamma_0\delta_0) + (\beta_1 + \gamma_1\delta_0) \times mp_t + (\beta_2 + \gamma_0\delta_1) \times mb_{i,t} + \tag{B.3}$$

$$(\beta_3 + \gamma_1\delta_1) \times mb_{i,t} \times mp_t + \nu_t + \varepsilon_{i,t} \tag{B.4}$$

If I ignore c_t, the probability limit of the Pooled OLS estimator for the interaction effect of monetary policy and market-to-book equity will be:

$$plim\ \hat{\beta}_3 = \beta_3 + \gamma_1 \times \frac{Cov(mb_{i,t}, c_t)}{Var(mb_{i,t})} \tag{B.5}$$

The Pooled OLS estimator is biased and inconsistent, if γ_1 and δ_1 are different from zero. Moreover, given that mb and valuations are likely positively correlated, the estimator of the effects of monetary policy on stock returns will be overestimated (Consistent with the results in table 4 later).

B.2 Correcting the bias with Fixed Effects

To construct the fixed effects specification we calculate the average of all variables in equation B.1 and subtract them from the equation. Formally:

$$\ddot{r}_{t,i} = \beta_2 \times \ddot{mb}_{i,t} + \beta_3 \times (mp_t \ddot{\times} mb_{i,t}) + \ddot{\varepsilon}_{i,t} \tag{B.6}$$

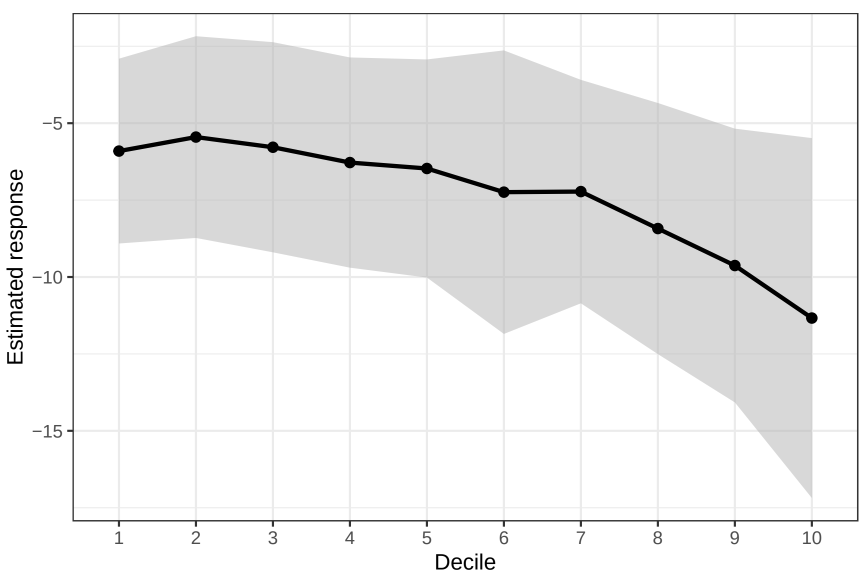
Where $\ddot{x}_{i,t} = x_{i,t} - \bar{x}_t$ and $\bar{x}_t = N^{-1} \sum_{i=1}^{N} x_{i,t}$.

Notice that because I have an omitted variable which is only time-dependent I will not be able to differentiate between its effects and the effects of the other time-dependent variables which I actually observe, such as mp_t. In fact, because of that I cannot estimate the true partial effect of monetary policy on stock returns using time fixed effects, but only the differences in effects with an increasing market-to-book equity.

Likewise, I can repeat this analysis by assuming that there is a unobserved effect which is constant over time but varies across firms. This could be, for example, managerial quality or industry. To account for this effect I demean the variables averaging over the firm's dimension.

C Further empirical results

Figure C.1: Portfolio reaction of MBE sorted portfolios using Fama and French portfolios



The figure shows the average reaction of the 10 decile portfolios sorted by market-to-book equity using NS surprises against the mean market-to-book equity. 10% confidence intervals are drawn around the point estimation. The samples goes from January 1990 to December 2018.

Table C.1: Reaction of spread portfolios to monetary policy surprises using Fama and French portfolios

	10% - 10%	30% - 30%	50% - 50%	90% - 10%	10% - 90%
mps	-5.38^{*}	-4.04^{**}	-2.76^{**}	-1.61^{*}	-4.37^{*}
	(2.77)	(1.93)	(1.28)	(0.93)	(2.42)
Constant	-0.06	-0.01	-0.01	-0.03	-0.03
	(0.05)	(0.03)	(0.02)	(0.03)	(0.04)
N	255	255	255	255	255
R^2	0.04	0.07	0.07	0.02	0.06

The table estimates the regression $r_t^s = \alpha + \beta \times mps_t + \varepsilon_{i,t}$ using the sample from January 1990 to December 2018, where r_t^s is the return of the spread portfolio. The spread portfolios are formed by sorting firms according to the market-to-book ratio and subtracting the 50%, 30% and 10% highest from the lowest companies each period. The last two columns show the spread portfolio of the 90% highest companies and the 10% lowest and vice-versa. White standard errors are computed. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table C.2: Summary Statistics VAR variables

	Variable	RR	DRF	R-Bill	SPREAD	DP	EX
	mean	0.09	0.00	-0.08	1.28	-3.71	0.32
S&P500	sd	0.36	0.06	1.09	1.17	0.42	4.31
	max	2.00	0.35	4.61	3.40	. -2.77	11.96
	min	-0.95	-0.45	-4.22	-3.07	-4.50	-25.14
	mean	0.09	0.00	-0.08	1.28	-3.52	0.26
Russel Value	sd	0.36	0.06	1.09	1.17	0.27	4.20
	max	2.00	0.35	4.61	3.40	-2.93	10.87
	min	-0.95	-0.45	-4.22	-3.07	-4.02	-23.51
	mean	0.09	0.00	-0.08	1.28	-4.18	0.36
Russel Growth	sd	0.36	0.06	1.09	1.17	0.47	4.92
	max	2.00	0.35	4.61	3.40	-3.43	12.91
	min	-0.95	-0.45	-4.22	-3.07	-5.88	-27.13

The table shows the summary statistics of the variables used in the first-order VAR: The real interest rate (RR), change in the 3-month bill rate (DRF), the relative bill rate (R-Bill), the spread between the 10-year and 1-month Treasury yield (SPREAD), the log of dividend price ratio (DP) and excess return (EX). The sample goes from Jan-1979 to Dec-2018.

Table C.3: Excess return regression on state variables

	S&P500	Russel Value	Russel Growth
RR	-0.22	-0.12	-0.43
	(0.59)	(0.58)	(0.67)
DRF	-0.19	1.45	-1.08
	(3.38)	(3.29)	(3.83)
R-Bill	-0.10	0.003	-0.25
	(0.23)	(0.23)	(0.26)
SPREAD	0.13	0.21	0.03
	(0.21)	(0.20)	(0.23)
DP	0.004	0.01	0.01^{**}
	(0.005)	(0.01)	(0.005)
EX	0.05	0.07	0.06
	(0.05)	(0.05)	(0.05)
N	479	479	479
R^2	0.01	0.01	0.02

The table shows the regression of excess equity returns on lagged excess equity return, the real interest rate, the relative bill rate, the change in the 3-month bill rate, the dividend price ratio, and the spread between the 10-year and 1-month Treasury yields. All variables are demeaned. The sample period goes from Jan-1979 to Dec-2018. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

References

Bernanke, Ben S, Mark Gertler, and Simon Gilchrist (1999) "The financial accelerator in a quantitative business cycle framework," *Handbook of macroeconomics*, 1, 1341–1393.

Bernanke, Ben S and Kenneth N Kuttner (2005) "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of finance*, 60 (3), 1221–1257.

Campbell, John Y (1991) "A variance decomposition for stock returns," *The economic journal*, 101 (405), 157–179.

Campbell, John Y and John Ammer (1993) "What moves the stock and bond markets? A variance decomposition for long-term asset returns," *The journal of finance*, 48 (1), 3–37.

Campbell, John Y and Robert J Shiller (1988) "The dividend-price ratio and expectations of future dividends and discount factors," *The Review of Financial Studies*, 1 (3), 195–228.

Carlson, Murray, Adlai Fisher, and Ron Giammarino (2004) "Corporate investment and asset price dynamics: Implications for the cross-section of returns," *The Journal of Finance*, 59 (6), 2577–2603.

Chava, Sudheer and Alex Hsu (2020) "Financial constraints, monetary policy shocks, and the cross-section of equity returns," *The Review of Financial Studies*, 33 (9), 4367–4402.

Chen, Long and Xinlei Zhao (2009) "Return decomposition," *The Review of Financial Studies*, 22 (12), 5213–5249.

Chen, Zhanhui (2022) "Inferring Stock Duration Around FOMC Surprises: Estimates and Implications," *Journal of Financial and Quantitative Analysis*, 57 (2), 669–703.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico (2023) "Monetary policy, corporate finance, and investment," *Journal of the European Economic Association*, jvad009.

Cochrane, John H (2009) *Asset pricing: Revised edition*: Princeton university press.

Cornell, Bradford (1999) "Risk, duration, and capital budgeting: New evidence on some old questions," *The Journal of Business*, 72 (2), 183–200.

Da, Zhi (2009) "Cash flow, consumption risk, and the cross-section of stock returns," *The Journal of Finance*, 64 (2), 923–956.

Davis, James L (1996) "The cross-section of stock returns and survivorship bias: Evidence from delisted stocks," *The Quarterly Review of Economics and Finance*, 36 (3), 365–375.

Dechow, Patricia M, Richard G Sloan, and Mark T Soliman (2004) "Implied equity duration: A new measure of equity risk," *Review of Accounting Studies*, 9 (2), 197–228.

Ehrmann, Michael and Marcel Fratzscher (2004) "Taking stock: Monetary policy transmission to equity markets," *Journal of Money, Credit and Banking*, 719–737.

Fama, Eugene F and Kenneth R French (1993) "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 33 (1), 3–56.

Gonçalves, Andrei S (2021) "The short duration premium," *Journal of Financial economics*, 141 (3), 919–945.

Gormsen, Niels Joachim and Eben Lazarus (2023) "Duration-Driven Returns," *The Journal of Finance*, 78 (3), 1393–1447.

Gürkaynak, Refet S, Brian Sack, and Eric T Swanson (2005) "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*.

Gürkaynak, Refet, Hatice Gökçe Karasoy-Can, and Sang Seok Lee (2022) "Stock market's assessment of monetary policy transmission: The cash flow effect," *The Journal of Finance*, 77 (4), 2375–2421.

Ippolito, Filippo, Ali K Ozdagli, and Ander Perez-Orive (2018) "The transmission of monetary policy through bank lending: The floating rate channel," *Journal of Monetary Economics*, 95, 49–71.

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

Knox, Benjamin and Annette Vissing-Jorgensen (2022) "A stock return decomposition using observables."

Kuttner, Kenneth N (2001) "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of monetary economics*, 47 (3), 523–544.

Lettau, Martin and Jessica A Wachter (2007) "Why is long-horizon equity less risky? A duration-based explanation of the value premium," *The Journal of Finance*, 62 (1), 55–92.

——— (2011) "The term structures of equity and interest rates," *Journal of Financial Economics*, 101 (1), 90–113.

Liu, Laura Xiaolei, Toni M Whited, and Lu Zhang (2009) "Investment-based expected stock returns," *Journal of Political Economy*, 117 (6), 1105–1139.

Maio, Paulo (2014) "Another look at the stock return response to monetary policy actions," *Review of Finance*, 18 (1), 321–371.

Nakamura, Emi and Jón Steinsson (2018) "Identification in macroeconomics," *Journal of Economic Perspectives*, 32 (3), 59–86.

Ozdagli, Ali K (2018) "Financial frictions and the stock price reaction to monetary policy," *The Review of Financial Studies*, 31 (10), 3895–3936.

Piazzesi, Monika and Eric T Swanson (2008) "Futures prices as risk-adjusted forecasts of monetary policy," *Journal of Monetary Economics*, 55 (4), 677–691.

Schauer, Catharina, Ralf Elsas, and Nikolas Breitkopf (2019) "A new measure of financial constraints applicable to private and public firms," *Journal of Banking & Finance*, 101, 270–295.

Swedroe, Larry (2019) "The short duration premium," https://alphaarchitect.com/2019/09/the-short-duration-premium/, September, Alpha architect (accessed 25/07/2023).

Van Binsbergen, Jules H and Ralph SJ Koijen (2017) "The term structure of returns: Facts and theory," *Journal of Financial Economics*, 124 (1), 1–21.

Vuolteenaho, Tuomo (2002) "What drives firm-level stock returns?" *The Journal of Finance*, 57 (1), 233–264.

Weber, Michael (2018) "Cash flow duration and the term structure of equity returns," *Journal of Financial Economics*, 128 (3), 486–503.

Zhang, Lu (2005) "The value premium," *The Journal of Finance*, 60 (1), 67–103.