Cash Flow Duration, Financial Constraints, and the Stock Market Sensitivity to Monetary Policy*

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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 cash flow duration, which contradicts earlier studies arguing that the degree of financial constraint is the predominant driver. Higher duration induces a larger exposure to discount rates news, which is more sensitivity to monetary policy than cash flow news. Finally, these empirical findings can be explained by a reduced-form asset pricing model in which firms heterogeneity is modelled by cash flow duration. The model generates a higher sensitivity of growth stocks to monetary policy while preserving the value premium.

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

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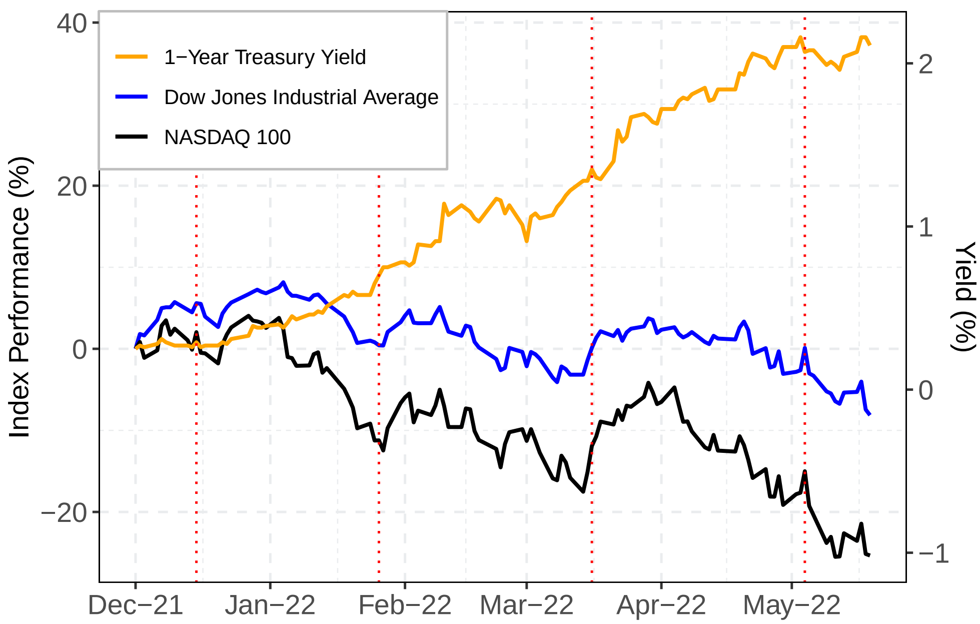
1 Introduction

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. This gap in the literature can be attributed to the predominant focus within the asset pricing literature on explaining the value premium (Pätäri and Leivo, 2017), and the conflicting evidence provided by the macro-finance literature (Ehrmann and Fratzscher, 2004; Maio, 2014). However, considering the extensive evidence highlighting the distinct characteristics of growth and value stocks, it is reasonable to expect that they exhibit varying responses to monetary policy.

To illustrate that growth and value stocks might react differently to monetary policy, Figure 1 shows the path of the Dow Jones Industrial Average (DJIA), NASDAQ and the 1-year Treasury yield from December 2021 to June 2022. In this period, which is characterized by four monetary policy announcements by the Federal Open Market Committee (FOMC), 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, this figure does not provide causal evidence of monetary policy on stock returns, since other factors could have driven the stock prices and the Treasury yields.

To infer causal effects this paper uses a high-frequency approach to provide new evidence that growth stocks exhibit a greater sensitivity to monetary policy than value stocks. I adopt the monetary policy surprise proposed by Nakamura and Steinsson (2018), which captures target and forward guidance surprises, with the latter being specially important for the period of the zero lower bound. My analysis reveals statistically and economically significant differences in the sensitivity of growth and value stocks. For instance, a change of one standard deviation in market-to-book equity corresponds to an approximate 2.2 percentage points drop in returns following a monetary policy tightening. The heightened sensitivity of growth stocks is evident 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 more than 10 days. However, a regression of monthly returns on the daily monetary policy surprises cannot capture this sensitivity, which is one of the reasons previous studies have failed to find the same result.

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.

The reason that growth equities are more sensitivity to monetary policy may be attributed to their characterization as longer-duration assets. As their cash flow payments are, on average, further 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 recognized among industry professionals (Swedroe, 2019), a rigorous academic investigation into the specific mechanisms by which monetary policy influences growth and value stocks, particularly through the lens of duration, remains unexplored. 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. These explanations suggest that a firm's sensitivity to external financing influences how it is affected by monetary policy, which is a point supported by existing research. However, it remains uncertain whether firms with financial constraints feel a greater impact than those without (Ozdagli, 2018; Chava and Hsu, 2020).

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 (Ehrmann and Fratzscher, 2004). Given that cash flow duration and financial constraints are the two most widespread economic reasons for the different reactions of growth and value stocks, I focus on examining both of them as possible explanations. 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 are not linked to the responses of growth and value stocks.

Since duration is the derivative of the price with respect to discount rates, the duration channel implies that monetary policy primarily affects stock prices through changes in risk premium or risk-free rate. In contrast, a stronger impact of policy shocks on the cash flow expectations should push back the duration channel in favour of the cash flow channel, whose main driver should be financial constraints. Hence, in the second part of the paper I decompose the excess stock returns in risk premium, risk-free rate, and cash flow news. After log-linearizing the excess returns I infer the effects of monetary policy on the long-run news from the S&P500 using a vector auto-regressive model. This exercise confirms that discount rate news is the main driver of stock price responses to monetary policy. In addition, I demonstrate that real rates play a relatively minor role in this result, i.e. the risk premium is the main driving channel through which monetary policy shocks are transmitted to the stock market, a fact previously documented by Bernanke and Kuttner (2005).

To understand the economic factors driving the response of growth and value stocks, my analysis expands the log-linearization to the Russell Value and Growth Indexes, as well as Fama and French's market-to-book equity sorted portfolios. I find that for both value and growth stocks, the risk premium is the main channel through which monetary policy is transmitted. However, this impact is more pronounced in growth stocks. This can be attributed to the superior predictive power of growth stocks' dividend yields on their future excess returns, indicating that discount rates more accurately account for their price fluctuations. Golez and Koudijs (2023) show that the predictability of excess returns by dividend yields and stocks' cash flow duration are positively related. Consistently, these findings complement my firm-level evidence suggesting that cash flow duration is an important transmission channel of monetary policy to the cross-section of stock returns.

Finally, 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 it to capture the duration effects from monetary policy shocks. I follow the modelling strategy of Pflueger and Rinaldi (2022) and include high-frequency monetary policy shocks in a quarterly frequency framework, with policy surprises arising at the end of each quarter. In the model, firms with higher price-dividend ratio have longer cash-flow duration and so are more exposed to shocks on discount rates, the main driving channel of monetary policy to stock returns. This additional feature in the model does not change the key property of the model, implying that the stronger response of growth stocks to monetary policy is in line with the value premium. Hence, a model which solely accounts for the duration of stocks can replicate the documented sensitivity of growth and value stocks to monetary policy.

This paper aims to resolve a longstanding debate within the macro-finance literature, where limited empirical evidence has been presented to substantiate the duration argument as an explanation for different responses of growth and value stocks. 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.[1] 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), 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

[1] Daniel and Titman (2006) dispute the argument that past fundamental performance influence future common stock returns.

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.[2] 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.

In addition, my paper contributes to the vast literature of studies of equity duration (Cornell, 1999; Dechow et al., 2004; Da, 2009; Weber, 2018; Gonçalves, 2021; Chen, 2022; Gormsen and Lazarus, 2023). My duration proxy is the same used by Gonçalves (2021), who employs 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-section of stock returns. Ozdagli (2018) provides evidence that high duration stocks are more sensitive to monetary policy, but he does not link these results to market-to-book equity. Finally, 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).

On the financial constraints side, a variety of papers have analyzed how cross-section responses of stock returns 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.

Finally, to understand the stock price movements, I use a log linear-approximation of stock returns and estimate the long-run news using a VAR (Campbell and Shiller, 1988;

[2]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.

Campbell, 1991; Campbell and Ammer, 1993; Vuolteenaho, 2002). 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.

Overall, this paper provides substantial new evidence on the responses of growth and value stocks to monetary policy, elucidating the underlying economic reasons for their sensitivity. My results have strong implications for the monetary economics literature, highlighting that cash flow duration is an important mechanism through which monetary policy spreads to the equity market. It also confirms the existence of the credit channel implied by different economic models, although financial constraints are unrelated to the sensitivity of growth and value stocks to monetary policy. Furthermore, this paper contributes to the asset pricing literature by underscoring the significance of duration as a key determinant driving the different dynamics observed in growth and value stocks.

This paper is organized as follows: Section 2 provides an overview of the monetary policy, accounting data, and stock market data used in the study. Section 3 explores the sensitivity of growth and value stocks to monetary policy across various levels of aggregation. It also explains why previous studies have failed to uncover similar results and examines how far in the future the responses of growth and value stocks go. Section 4 investigates the economic mechanisms driving the differential sensitivity of growth and value stocks, with a focus on analyzing cash flow duration and financial constraints. Section 5 derives the excess return log-linearization and applies it to a regression of discount rates and cash flow news on monetary policy. Section 6 presents the duration based asset pricing model.

2 Data and Summary Statistics

2.1 High-Frequency Monetary Policy Surprises

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 (Kuttner, 2001; Gürkaynak et al., 2005; Nakamura and Steinsson, 2018). I use the 30-minutes change around an FOMC annoucement in the rate implied by the current-month and the three-months funds future contract, and the prices of eurodollars future contracts with maturity of up to a year and extract their first principal component (Nakamura and Steinsson, 2018). This discrete change in rates can be associated with a monetary policy surprise, because the prices will only move provided the FOMC released unexpected information.[3] The use of interest rates instruments with higher maturity is crucial for the analysis during the zero lower bound. Since the target rate in the United States did not move throughout this period, monetary policy maintained its effectiveness only through forward guidance. Hence, my monetary policy surprise accounts for both, target and forward guidance shocks. The complete derivation of the monetary policy surprise is shown in Appendix.

2.2 Firm-Level Data

To construct my unbalanced panel dataset I extract quarterly accounting data from Compustat and stock prices from CRSP. The market-to-book equity is generated for each firm in each quarter based on the definition provided by Daniel and Titman (2006). 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 step 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. Consistent with Fama and French (1993) I include stocks exchanged in the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11. To ensure liquidity, stocks with a price less than \$5 or a market capitalization less than \$10 million are dropped (Daniel and Titman, 2006; Chava and Hsu, 2020). This yields a total of 512,741 data points with 9,096 different firms.

2.3 Aggregate Data

To investigate the effects of policy surprises on aggregate measures of valuation and stock returns, I extract daily prices and quarterly aggregate multiples for the S&P500, the Russel 1000, and the Russel Growth and Value Index from Bloomberg. The simple return is computed using the closing prices of the FOMC announcement day and the closing price of the preceding day. Table 1 shows the summary statistics of the four stock indexes.

[3] Bauer and Swanson (2023) find that these monetary policy surprises are correlated with macroeconomic variables that predate the FOMC announcements. However, they show that using a robust monetary policy surprise does not change the results for financial market data.

Table 1: 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, quarterly price-to-book (P/B), and price-to-earnings (P/E) ratio for the S&P500, Russel 1000, Russel 1000 Value, and Russel 1000 Growth. The sample goes from January 1990 to December 2018.

The difference in numbers of observations is due to data availability in Bloomberg. For example, while the valuation data of the S&P500 starts in 1990, the valuation ratios of the Russel Indexes start in 1995. The growth index has higher valuation ratios than the value index. The mean price-to-book ratio is about two times as high as the price-to-book 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 Sensitivity of Growth and Value Stocks

3.1 Daily Responses

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 2 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. However, their surprise measure does not account for forward guidance.

To analyze 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 2 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 around 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 significant.

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 important when running a panel regression, as unobserved time-varying variables could bias the coefficients. Moreover, in the beginning of the 21th century valuations were in record levels. Therefore, the results could be driven by the market valuation increase in this period. To evaluate the effects of time-varying aggregate valuation I regress the one-day returns on valuations interacted with monetary policy surprises, where valuations are measure by price-to-book and price-earnings ratio. Table 2 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 2: Reaction of stock indexes to monetary policy surprises and valuation ratios

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)	
pb*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 (price-to-book or price-earnings ratio). The coefficients for pb and pe, as well as the constant, have been omitted for clarity in visualization. White standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

3.1.2 Panel Regression

In this section I evaluate the response of growth and value firms to monetary policy. Although time-varying valuations do not seem to be a concern, other time or cross-sectional varying variables might confound the results of a pooled OLS. 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 in the regression 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.[4]

Table 3 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 7.6%. 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 up to 1.06 percentage points. This means that the stock price of a firm with mean market-to-book equity drops on average 7.4% 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 10.2%. These examples highlight the economic significance of the results.

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

	(1)	(2)	(3)	(4)	(5)	(6)
mb		0.0001	-0.02^{*}	0.002	-0.02^{*}	-0.04^{***}
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
mps	-7.61^{***}	-4.97^{**}	-4.87^{**}			5.32^{***}
	(2.12)	(2.06)	(2.01)			(1.85)
mb*mps		-0.98^{***}	-1.06^{***}	-0.79^{***}	-0.89^{***}	-0.51^{***}
		(0.34)	(0.32)	(0.30)	(0.29)	(0.20)
Constant	0.24^{***}	0.24^{***}				
	(0.06)	(0.06)				
N	512,741	512,741	512,741	512,741	512,741	512,739
R^2	0.004	0.004	0.15	0.05	0.19	0.82
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. Column

[4] In Appendix B I show how the regression design avoids the problems of unobserved effects.

(6) re-runs the regression using beta-adjusted stock returns (returns minus the expected return according to the CAPM), as suggested by MacKinlay (1997). I estimate the betas using daily returns from Jan-1926 to Dec-2018. 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 more than three quarters of the firm-level variation in daily stock returns that is not accounted for in the CAPM.

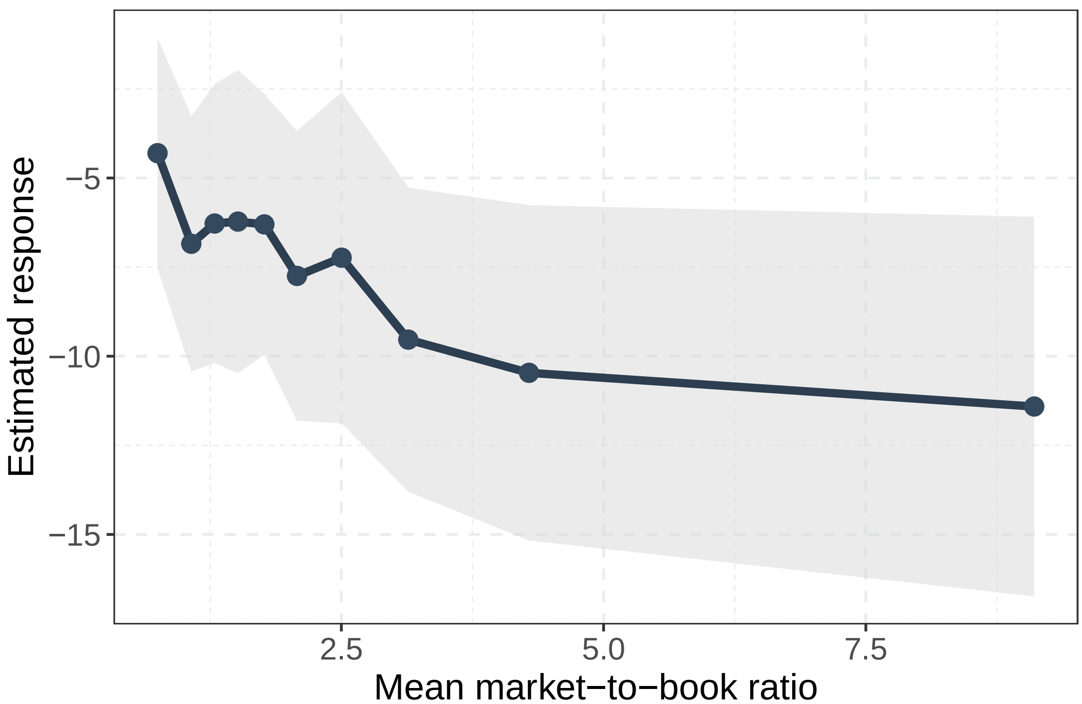
To investigate the robustness of the results I re-run the regressions controlling for size, profitability, and market leverage. I also repeat the regression controlling for dummies of the period commonly referred to as dotcom bubble and the zero lower bound, since these two periods are included in the sample. Columns (1) and (2) of Table C.1 show the coefficients with and without fixed effects when using different controls. The coefficients remain economically and statistically significant. Furthermore, as columns (3) to (6) demonstrate the period of the dotcom bubble does not impact my findings, nor does the zero lower bound, since the monetary policy surprises capture forward guidance surprises.

3.1.3 Portfolio-Level Results

Several studies advocate the use portfolio sorts when working with cross-sectional stock returns, because portfolios are less susceptible to idiosyncratic noise (Cochrane, 2009). Also, by dynamically adjusting the portfolios each quarter the unobserved effects are no longer a problem. Another advantage is that portfolio sorts enable to discover the presence of non-linear effects. I group the firm-level sample in 10 equal-size portfolios sorted by their lagged market-to-book equity in each quarter. For each portfolio I estimate the average daily raw return in each FOMC announcement day.

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. Specifically, the portfolio with the lowest mean market-to-book equity experiences an average loss of 4.3 percentage points, whereas the portfolio with the highest mean market-to-book equity loses, on average, 11.4 percentage points. Notably, this relationship exhibits non-linearity: the difference in responses between the first and second deciles is 2.5 percentage points, while the difference between the last two deciles is less than 1 percentage point. However, the market-to-book equity difference between the first two portfolios is merely 0.4, significantly lower than the 4.8 difference between the last two mean market-to-book equity portfolios. 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 quantile 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.

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.

Table 4 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 C.1 and Table C.2 in Appendix show the results of the same portfolio analysis using Fama and French portfolios.[5] The results are in line with the panel regression and

[5]The data was downloaded from Ken French's Website.

the portfolio sorts, providing evidence that these findings are independent of the sample construction.

Table 4: Reaction of spread portfolios to monetary policy surprises

	10% − 10%	30% − 30%	50% − 50%	90% − 10%	10% − 90%
mps	-7.11^{***}	-4.66^{**}	-3.29^{**}	-3.70^{***}	-4.20^{**}
	(2.60)	(1.90)	(1.41)	(1.15)	(1.93)
Constant	-0.11^{*}	−0.05	−0.03	-0.11^{**}	−0.01
	(0.06)	(0.04)	(0.03)	(0.04)	(0.04)
N	255	255	255	255	255
R^2	0.08	0.08	0.08	0.05	0.07

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. Maio (2014) conducted a monthly analysis to investigate whether growth or value stocks react more to monetary policy. The conclusion on the first part of the paper, that growth stocks react stronger to monetary policy than value stocks, contradicts his findings. 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 confounding variables. Monetary policy is highly endogenous, because the Fed does its best to react to economic conditions. The same conditions that affect stock prices.

Table 5: 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.

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.[6] Panel A from Table 5 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

[6] 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.

stocks are more reactive to monetary policy. Panel B re-runs his results starting in 1990, the 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 6 repeats the regressions from Table 5 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. This result is not surprising given that decreasing the frequency of returns increases the noise in the regression, which is indicated by the very low R-squared.

Table 6: 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. Columns (1) to (3) are the returns of the 10%, 20% and 30% spread portfolios, respectively. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

3.2.2 Dynamic Response of Stock Returns to Policy Surprises

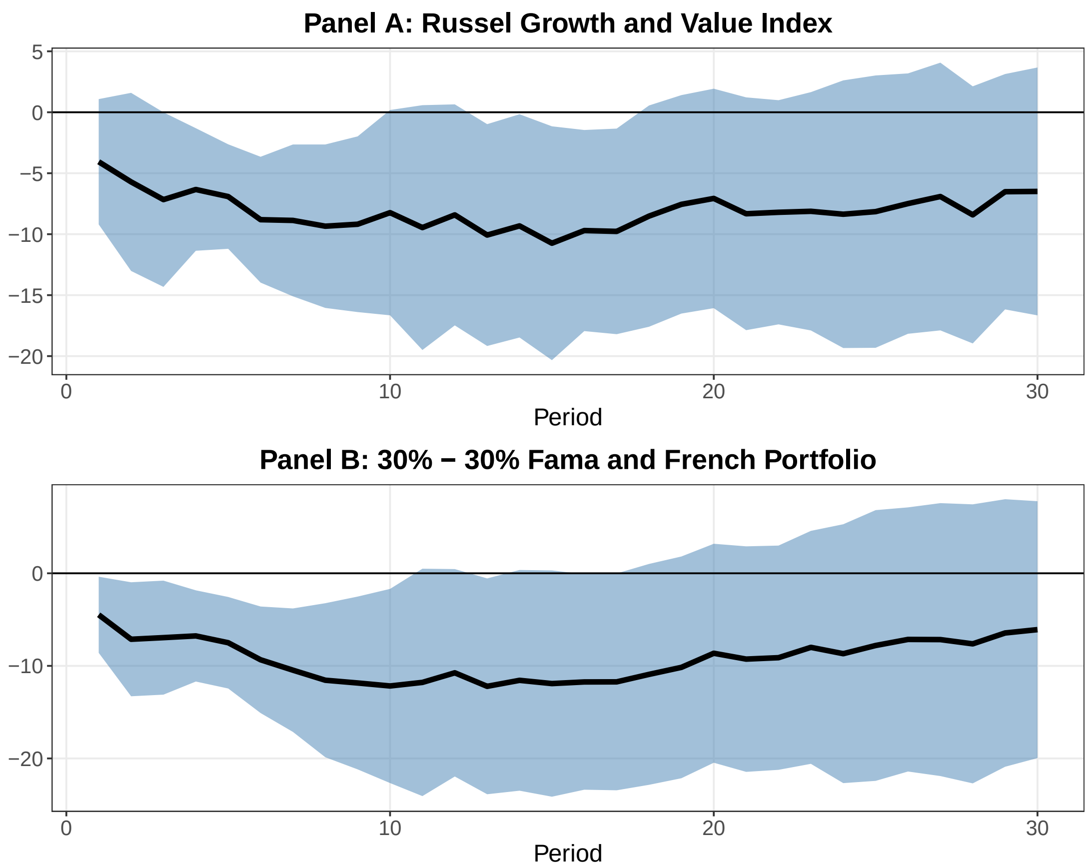
The analysis using a monthly frequency raises the question how long do the different policy responses of stock returns last for. To answer this question I regress the spread returns k-days ahead of the FOMC announcement on the policy surprise:

$$r_{t \to k}^s = \alpha + \beta \times mps_t + \varepsilon_t$$

Figure 3 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 sensitivity of growth stocks to monetary policy raises the question of what economic mechanism explains this phenomenon. 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. There is few evidence on the magnitude of this sensitivity after a monetary policy shock 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 concepts to the firms' capacity to access external funding.

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 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. The median duration in the final sample is 48 and so slightly higher than the duration reported by Gonçalves (2021) of 39. To analyze whether duration can explain the responses of growth and value stocks to monetary policy, I conduct a similar panel regression analysis as in Table 3 with time and firms fixed effects. As the duration distribution is highly skewed I run the regression using log duration.

Table 7 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 of a firm, 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, ceteris paribus, by 2.78 percentage points. Column 2 shows that the effect of market-to-book equity on monetary policy responses vanishes once I control for duration. Therefore, cash flow duration explains the response of cross-sectional stock returns which was previously captured by market-to-book equity. This result confirms that the responses of growth and value stocks are in fact driven by their cash flow duration.

Table 7: Panel regressions including duration and financial constraints

	(1)	(2)	(3)	(4)	(5)
log dur	−0.06	−0.04			−0.06
	(0.05)	(0.04)			(0.04)
mb		−0.01		−0.01	−0.02
		(0.01)		(0.01)	(0.01)
log dur*mps	−2.78***	−2.39***			−2.62***
	(0.79)	(0.67)			(0.73)
mb*mps		−0.26		−0.52***	−0.04
		(0.19)		(0.20)	(0.16)
FC			0.01	0.01	−0.01
			(0.04)	(0.04)	(0.05)
FC*mps			3.22***	2.68***	2.28**
			(1.18)	(1.01)	(0.98)
N	271,678	271,678	301,382	301,382	230,608
R^2	0.63	0.63	0.56	0.56	0.67

The table estimates the regression of returns on market-tobook 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

Several studies have proposed different measures of financial constraint. I follow Gürkaynak et al. (2022) and use the financial constraint measure developed by Schauer et al. (2019). They use 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, such as the KZ, the WW, and the SA index. After constructing the financial constraint index, I follow Gürkaynak et al. (2022) and 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. 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 7 shows that financial constraints have a positive and significant effect on the sensitivity of stock returns to monetary policy. Since the effects of monetary policy on stock returns is negative, financially constrained firms respond, ceteris paribus, 3 percentage points less to monetary policy. This result is in line with Ozdagli (2018) and Ottonello and Winberry (2020), who also find that financial constraints contribute to weaker responses 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. This 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.

Table C.3 in Appendix shows that the results on the financial constraints are robust towards using two alternative financial constraint measures, the KZ-index from Kaplan and Zingales (1997) and the SA-index from Hadlock and Pierce (2010). I construct the financial constraint dummy in the same way as before. The coefficients of the market-to-book equity remain unchanged after controlling for both financial constraint measures. Notably, the results using KZ- and SA-index suggest that firms facing financial constraints exhibit a stronger response to monetary policy, which contradicts the results obtained using the measure proposed by Schauer et al. (2019). However, it supports the conclusions drawn by Chava and Hsu (2020) and Cloyne et al. (2023). This finding contributes to the ongoing debate about the sensitivity of financially constrained firms to monetary policy, highlighting the challenge of reaching a consensus due to the diverse definitions of financial constraint and the various proxy measures employed.[7]

5 Policy Surprises and Stock Returns Decomposition

This section conducts a Campbell & Shiller decomposition to separate the excess return movements in risk premium, risk-free rate, and cash flow news. I use the news components to run a regression of excess return, cash flow, and real rate news of growth and value stocks on monetary policy surprises. 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) and Campbell (1991) 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:

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

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. I use a VAR(1) to estimate the

[7] A more in-depth study comparing the different financial constraint measures and their responses to monetary policy presents an interesting avenue for future research. However, such an investigation is beyond the scope of this paper.

future changes in expectations. Let z_t be a vector of state variables, which include the expected returns and the real rates. Then:

$$z_{t+1} = Az_t + \varepsilon_{t+1} \tag{2}$$

Equation 2 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:

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

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 (Campbell and Ammer, 1993; Bernanke and Kuttner, 2005; Maio, 2014). The estimation period is January 1990 to December 2018 and covers the whole period, in which the monetary policy surprises are available. Since the VAR specification requires a steady frequency, the model is estimated in a monthly frequency. Thus, I aggregate the monetary policy surprises by the sum of all surprises within each month. If there were no FOMC announcements within a month, the monetary policy surprise is zero.

An important caveat, pointed out by Chen and Zhao (2009), is that the decomposition will attribute too much weight to dividends, in case the VAR understates the predictability of expected returns. Consequently, caution is warranted, especially when the influence of the cash flow news is particularly pronounced. This is not the case in my analysis, as the main driver is indeed the discount rate news. Additionally, I incorporate the price-dividend ratio as a state variable, which according to Engsted et al. (2012) is essential for the decomposition to be valid. My main results are robust to different values of ρ and to including dividend growth as a state variable while identifying excess return news as residual.

To understand the effects of monetary policy on the news components, Bernanke and

Kuttner (2005) include monetary policy surprises in the VAR:

$$z_{t+1} = Az_t + \Phi mps_{t+1} + \nu_{t+1} \tag{3}$$

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. The effects of monetary policy surprises are given as follows:

$$\begin{aligned}
\eta_y &= s_y\Phi \\
\eta_r &= s_r(1-\rho A)^{-1}\Phi \\
\eta_{\tilde{y}} &= s_y\rho A(1-\rho A)^{-1}\Phi \\
\eta_d &= (s_y+s_r)(1-\rho A)^{-1}\Phi
\end{aligned} \tag{4}$$

The first column of Table 8 shows the estimated responses of the S&P500. The results demonstrate that the risk premium is the main driver of monetary policy: Around three quarters of the response of the S&P500 to monetary policy is significantly explained by changes in risk premium. Cash flow news and risk-free rate are less important. This outcome resembles the results of Bernanke and Kuttner (2005), even though they use a different policy surprise and a different sample period.

Table 8: Breakdown of monetary policy effects on unexpected excess returns

	S&P500	Russel Value	Russel Growth
Current excess return	-20.78***	-17.48***	-24.62***
	(6.03)	(5.97)	(6.79)
Future excess returns	13.02***	8.35**	24.34***
	(4.74)	(3.76)	(9.03)
Real interest rate	1.99*	1.99*	1.99*
	(1.02)	(1.02)	(1.02)
Dividends	-5.77**	-7.14*	1.71
	(3.35)	(5.97)	(6.79)

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-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.

5.2 Effects of Monetary Policy on Growth and Value News

To conduct the Campbell & Shiller decomposition on growth and value stocks I proceed akin to the S&P500 decomposition. The state variables in the VAR remain the same except for the dividend yields and expected returns which are updated accordingly for the growth and value portfolios. As the dividend yields of the Russel Index go back only to 1995, I extrapolate the data to beginning of 1990 using the fitted value of a regression of the dividend yields of the S&P500 on the dividend yields of both Russel indexes.[8] Moreover, I do not estimate the risk premium and interest rates separated, because real rates news are equal for all securities and dividend yields predictions from different portfolios should not yield different real rate revisions. To decompose discount rates news in risk premium and real rates I use the estimated real rate news from the S&P500.

Columns 2 and 3 of Table 8 present the estimated reactions of the Russell Value Index and Growth Index. The data indicates that growth stocks respond stronger to policy surprises than the overall market does, whereas the reactions of value stocks are lower, aligning with previous findings. The transmissions of monetary policy to value and growth stocks differ considerably, as the response of growth stocks is explained solely by future excess return news. Russel value stocks have a higher portion explained by cash flow news, although this

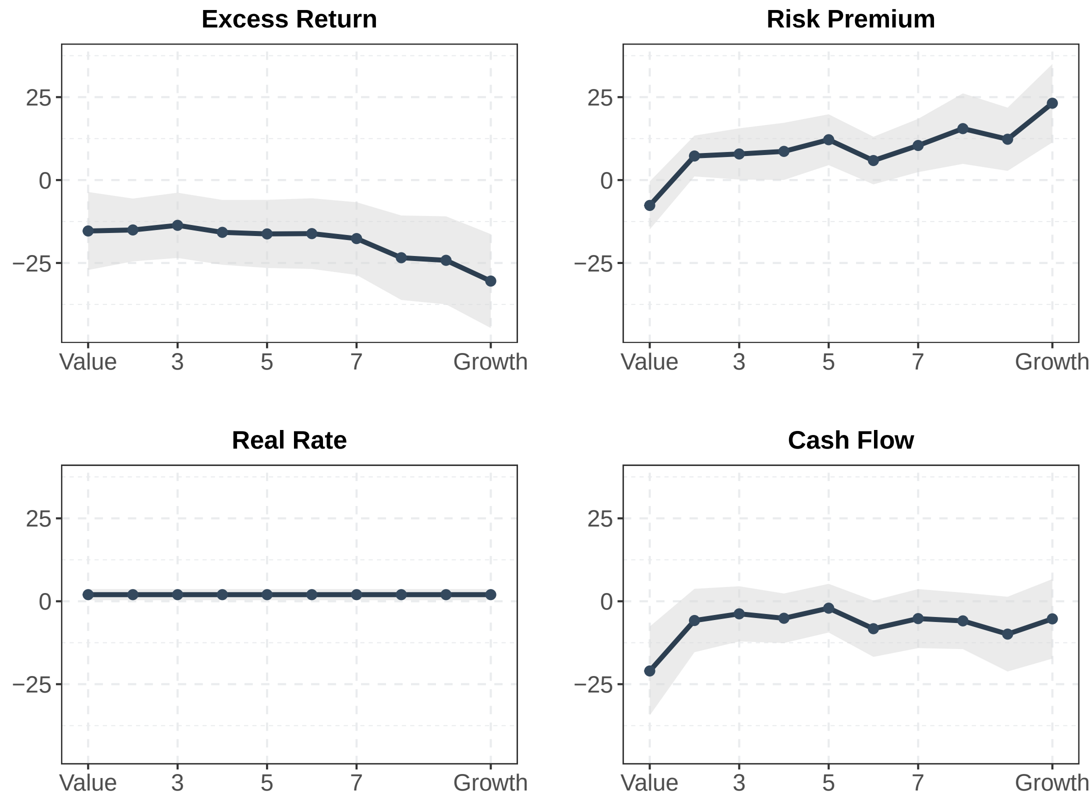
[8] The results remain robust to starting the sample in 1995.

portion is only marginally significant. These findings reinforce the notion that the discount rate news pertaining to growth stocks is more profoundly affected by monetary policy.

As the aggregate data might paint a limited picture, Figure 4 repeats the stock return decomposition for Fama and French portfolios sorted by market-to-book equity. The upper left figure shows that the response of the forecasting errors to monetary policy decreases with market-to-book equity. This indicates that stocks with higher market-to-book equity ratios experience more substantial price revisions. 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 risk premium is stronger for growth stocks. Cash flow news is slightly increasing in the lower deciles, but is mainly flat throughout the portfolio deciles and is not statistically significant. Overall, the portfolio sorts corroborates the findings from the index results and suggest that the disparate sensitivities observed across decile portfolios are primarily driven by discount rate news.

To provide evidence that my findings are robust, I repeat the Fama and French portfolios decompositions using (1) different values for ρ and (2) dividend growth as a state variable in the VAR while treating discount rate news as the residual component. As ρ is linked to the steady state price-dividend ratio, I estimate each portfolio's ρ using their mean price-dividend ratio. Figure C.3 in Appendix shows that the results remain almost identical to Figure 4 when using portfolio-specific ρ. Because monthly dividend yields are relatively small compared to annual dividend yields, ρ is close to 1 for all portfolios. To estimate the decomposition with dividend growth I include dividend growth as a further state variable in the VAR. The results, depicted in Appendix Figure C.4, again affirm the consistency of the findings. Because of the poor long-run forecastability of dividend growths, the discount rate news remain the primary driver of monetary policy responses, despite their identification as residuals. Hence, this robustness analysis substantiates the reliability of my findings, confirming that they stand resilient against potential criticisms of the Campbell & Shiller decomposition, such as those raised by Chen and Zhao (2009).

Figure 4: Response of unexpected excess returns to policy surprises using Fama and French



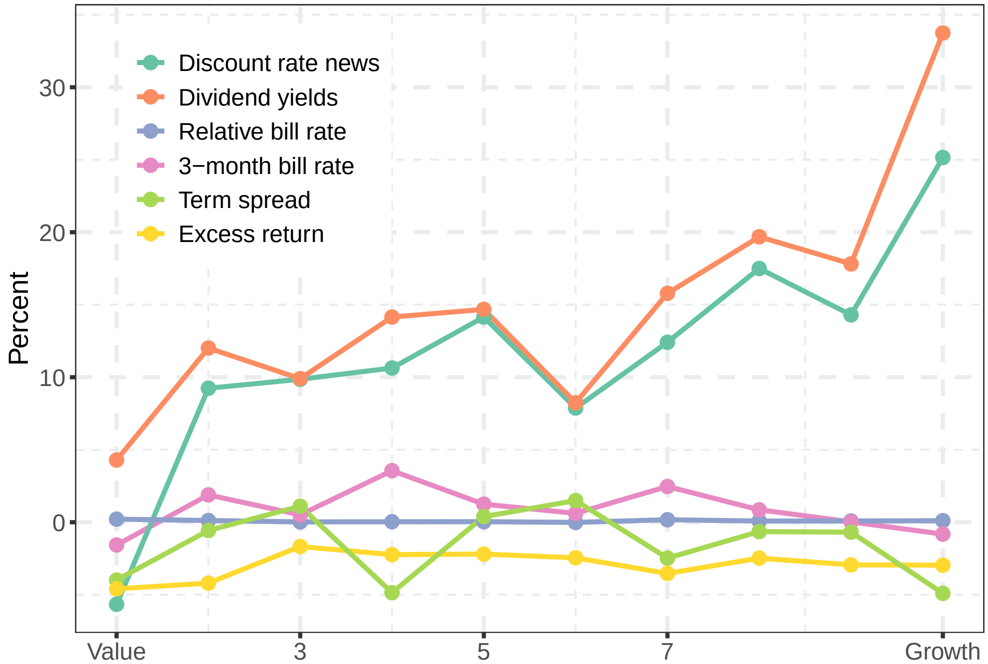
The figure shows the reaction of the news components of the unexpected excess returns for Fama and French portfolios. The portfolios are sorted from low to high market-to-book equity. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative bill rate, the change in the 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-1980 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 empirical findings in this section suggest that the credit channel of monetary policy — which is linked to a firm's cash flows — is not the primary determinant of the different sensitivities observed between growth and value stocks. In contrast, the cash flow duration of a firm is related to changes in discount rates, suggesting that the duration channel might be driving these results. To bolster this interpretation, I delve deeper into the underlying patterns in the risk premium. Notice that the long-run prediction of the excess return is given by the state variables. Monetary policy will affect the stock return predictions to the extend that it effects the state variables. Hence, it is possible to decompose the effects of monetary policy on future discount rates news into the effects of monetary policy surprises in each state variable. To elucidate this, recall from Equation 4 that the influence of monetary policy on risk premium news is quantified by $\eta_{\tilde{y}} = s_y \rho A(1-\rho A)^{-1} \cdot \Phi$. Here, the final asset response, $\eta_{\tilde{y}}$, is the sum of the product of two estimates: the contribution of each state variable to long-run forecastability of excess returns, represented by $s_y \rho A(1-\rho A)^{-1}$, and the impact of monetary policy on each state variable, denoted by Φ.

Figure 5 shows the product of the two estimates for each state variable together with the risk premium news across the ten decile portfolio. The Figure reveals that the heterogeneous response of growth and value stocks is predominantly explained by dividend yields. This is not surprising considering that with the exception of excess returns and dividend yields, all other state variables remain the same when running the VAR for the growth and value portfolios. In addition, past excess returns are not good predictors of future returns. Consequently, the phenomena that risk premium of growth stocks exhibits greater sensitivity to policy surprises than value stocks can be attributed to two main factors: First, the price-dividend ratio of growth stocks demonstrates a superior ability in forecasting future excess returns. Second the covariance of monetary policy and price-dividend ratio increases on market-to-book equity.

The fact that dividend yields are better predictors of growth stock returns is consistent with the duration effect. According to Golez and Koudijs (2023) discount rates become more important for asset price variation, the higher the duration. This consequently implies that price-dividend ratio can better predict future long-run expected returns. The reason why discount rates increase in importance is two-folded: First, expected returns are more persistent than dividend growth rates. Consequently, when the duration increases, expected returns portions of variation will become larger relative to dividend growth. Second, the variance of future expected returns increases with duration. Maio and Santa-Clara (2015) also find that return predictability is more important for growth stocks and argue in favour of the duration effect.

Figure 5: Dividend yields explains discount rate news



The figure shows the effects of monetary policy on the discount rates news on each of the 10 Fama and French decile portfolios. The other lines breaks down these effects on the policy response of each state variable of the VAR. The portfolios are sorted from low to high market-to-book equity. The VAR is estimated from Jan-1990 to Dec-2018.

6 Theoretical Framework

In this section I show how to reconcile my findings of value and growth stocks with a theoretical asset pricing model. The exercise serves two purposes: First, it demonstrates that a model that accounts solely for duration heterogeneity across firms can replicate my empirical results. Second, it shows that a model that encapsulates higher sensitivity of growth stocks to monetary policy is still in line with the existence of a value premium. In other words, the additional monetary policy dynamics do not hurt the model's ability to match quarterly stock market moments.

I start with a simplified version of the model from Lettau and Wachter (2011), which is the baseline asset pricing model on the behaviour of growth and value stocks, and models firms as portfolios of zero-coupon equities. Since inflation and nominal interest rates are not relevant to replicate my empirical findings, I do not model them explicitly. I then extend the model to account for monetary policy surprises.

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

$$\begin{aligned}
\Delta d_{t+1} &= z_t + \sigma_d \epsilon_{d,t+1} \\
z_{t+1} &= (1-\phi_z)g + \phi_z z_t + \sigma_z \epsilon_{z,t+1} \\
r^f_{t+1} &= (1-\phi_r)\bar{r}^f + \phi_r r^f_t + \sigma_r \epsilon_{r,t+1} \\
x_{t+1} &= (1-\phi_x)\bar{x} + \phi_x x_t + \sigma_x \epsilon_{x,t+1}
\end{aligned} \tag{5}$$

ϵ_t is a iid standard normal shocks.

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

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

Let $P_t^{(n)}$ 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 log price-dividend ratio of a zero-coupon equity is affine on the state variables (see Lettau and Wachter (2011) for the complete derivation):

$$\frac{P_t^{(n)}}{D_t} = \exp\left(A^{(n)} + B_z^{(n)}(z_t - g) + B_r^{(n)}(r^f_{t+1} - \bar{r}^f) + B_x^{(n)}(x_t - \bar{x})\right) \tag{6}$$

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

$$\begin{aligned}
B_x^{(n)} &= B_x^{(n-1)}\left(\phi_x - \rho_{dx}\sigma_x\right) - \sigma_d - B_z^{(n-1)}\rho_{dz}\sigma_z - B_r^{(n-1)}\rho_{dr}\sigma_r \\
A^{(n)} &= A^{(n-1)} - \bar{r}^f + g - V^{(n-1)}\bar{x} + \frac{1}{2}(V^{(n-1)})^2
\end{aligned}$$

with boundary conditions $B_x^{(0)} = A^{(0)} = 0$, and

$$V^{(n-1)} = \sigma_d + B_z^{(n-1)}\sigma_z + B_r^{(n-1)}\sigma_r + B_x^{(n-1)}\sigma_x$$

The aggregate market portfolio is the claim to all future dividends. Therefore, under certain parametric conditions the price dividend ratio of the market is

$$\frac{P_t}{D_t} = \sum_{n=1}^{\infty} \frac{P_t^{(n)}}{D_t} = \sum_{n=1}^{\infty} \exp\left(A^{(n)} + B_z^{(n)}(z_t - g) + B_r^{(n)}(r_{t+1}^f - \bar{r}^f) + B_x^{(n)}(x_t - \bar{x})\right) \tag{7}$$

The risk premium of a zero coupon equity depends on the loadings of the equity term structure. Because the correlation between dividend growth and price of risk is assumed to be zero, the equity premium is

$$E_t(R_{t+1}^{(n)} - R_{t+1}^f) \approx [\sigma_d + B_z^{(n-1)}\rho_{dz}\sigma_z + B_r^{(n-1)}\rho_{dr}\sigma_r]x_t$$

Where ρ_{dz} and ρ_{dr} denote the correlations of dividend growth with expected dividend growth and risk-free rate, respectively. The expression in parentheses can be interpreted as the quantity of risk, whereas x_t is the price risk. To understand how the model generates a value premium, notice that the condition $\rho_{dx} = 0$ implies that agents are indifferent about holding assets which only differ in their exposure to discount rate risks. This aspect is important, because in consumption-based models, such as the habits model from Campbell and Cochrane (1999) and the long-run risk model from Bansal and Yaron (2004), agents display aversion to discount rate risks. In such models, securities with longer-dated payouts are more vulnerable to discount rate risks, prompting agents to seek a substantial risk premium for holding these securities. Consequently, a negative correlation between the stochastic discount factor and discount rate risk results in a growth premium.

The second important condition in the model is $\rho_{dz} < 0$, implying that shocks to expected dividend growth serve as a hedge against actual dividend growth shocks. In this framework, high duration assets, which load more on dividend growth due to positive growth rates, become less risky and agents require a smaller risk premium to hold them. This condition ultimately gives rise to a value premium.

6.1 Identification of Monetary Policy

To include a high-frequency monetary policy shock I follow the modelling approach of Pflueger and Rinaldi (2022) and differentiate between low- and high-frequency variables. Specifically, I assume that at the conclusion of each quarter, there is a FOMC meeting that potentially yields a monetary policy surprise. To analyze the effects of these meetings, I distinguish between shocks before and after FOMC announcements. Variables prior to the FOMC announcement at time t are different from those post-FOMC at time $t-1$, as they encompass information from the shock at the period t excluding the FOMC decisions. The shock is defined as:

$$\epsilon_{i,t} = \epsilon_{i,t}^{pre} + \psi_i \epsilon_t^{MP} \tag{8}$$

where $i = d, r, z, x$. The high-frequency returns around monetary policy news are calculated using post- and pre-FOMC prices. I calibrate ψ_i based on a number of empirical studies. I set the effect of monetary policy shock on real rates ($\sigma_r \psi_r$) to 1.06 percent, which is the impact of monetary policy surprise on short-term real rate recorded by Nakamura and Steinsson (2018). The impact of monetary policy on price of risk is calibrated to 0.6 in line with Bauer et al. (2023), who show that a 10 basis points increase in monetary policy surprise, increases the price of risk by "a little less than half its standard deviation". To pin down the impact of monetary policy on expected dividend growth shocks I generate an empirical proxy of z_t using the consumption-dividend ratio analogous to Lettau and Wachter (2007) and regress it on monetary policy surprises. I find that a one unit increase in monetary policy surprises decreases z_t by 44 basis points. I assume that the dividend payment in the current quarter is not impacted by the FOMC decisions, making the post- and pre-FOMC dividend growth equal: $\Delta d_{t+1}^{pos} = \Delta d_{t+1}^{pre}$.[9] Finally, I match the standard deviation of ϵ_t^{MP} to the empirical standard deviation of monetary policy surprise of 0.04. All other parameters of the model are calibrated according to Lettau and Wachter (2011) and adjusted to quarterly frequency.

To gain intuition about the effects of monetary policy on the stock returns, one can derive the high-frequency log return of a zero-coupon equity analytically by subtracting the price dividend ratio before and after the monetary policy shock:

$$r^{(n)}{}_{t+1}^{hf} = [B_z^{(n)} \psi_z \varepsilon_{t+1}^{MP} + B_r^{(n)} \psi_r \varepsilon_{t+1}^{MP} + B_x^{(n)} \psi_x \varepsilon_{t+1}^{MP}] \tag{9}$$

Equation 9 shows that the log return on the zero coupon equity is linear on the monetary policy shocks. This relationship is particularly insightful, revealing that assets with higher maturities are more sensitive to monetary policy shocks, as the product of ψ and the loadings will be negative. This relationship implies that growth stocks are not only more sensitive to monetary policy due to discount rates effects, but also because of the sensitivity to expected dividend growth.

6.2 Growth and value portfolios

The construction of growth and value portfolios follows the methodology of Lettau and Wachter (2011), using a predetermined deterministic process for cash-flow shares. Specifi-

[9] Pflueger and Rinaldi (2022) make a similar assumption regarding the consumption and output in their model.

cally, a firm produces a portion s_t^i of the aggregate dividend, increasing at a steady quarterly rate of g_s — which is set to 5% — for the initial 100 quarters and then decreasing at the same rate for the subsequent 100 quarters. The maximum value of a share is $\bar{s} = \underline{s}(1+g_s)^{N/2}$ with $\underline{s}$ adjusted so the sum of all shares equals one. This modelling approach reflects the varying dividend contributions of firms at different stages of their life cycle. I simulate 200 firms over a 50-year span, which represents a full firm life cycle.

No-arbitrage implies that the price of each firm is its share of the aggregate dividend times its present value:

$$P_t^i = \sum_{n=1}^{\infty} s_{t+n}^i P_t^{(n)} \tag{10}$$

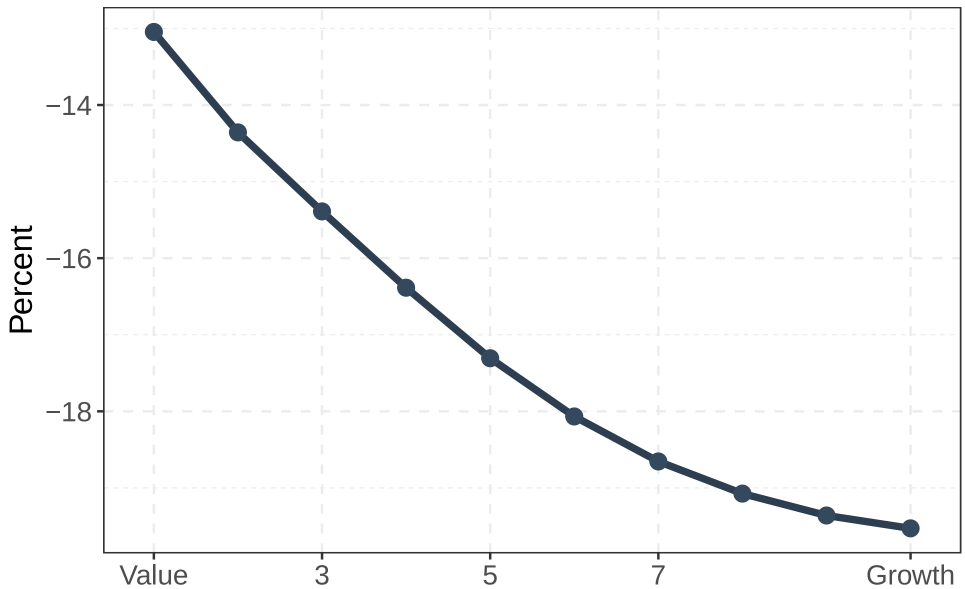
In this model, firms are categorized as value or growth based on their lagged price-to-dividend ratios. Value firms are defined by their low price-to-dividend ratios, indicating a higher proportion of dividends in the short term. Consequently, value firms represent assets with shorter duration. I simulate 50.000 quarters of data and create 10 decile portfolios averaging the firm returns within each portfolio.

6.3 Simulated results

Figure 6 shows the response of the 10 decile portfolios to monetary policy surprises for 50.000 quarter of simulated data. The response of the portfolios match the decreasing pattern found in the data, even though the responses are slightly higher compared to the data. Still, the model generates a spread return between the first and tenth decile of around 8 percentage points, similar to my empirical findings, as shown in Table 4. The reason for this pattern in the model is that a positive monetary policy shock impacts the price of risk and risk-free rate positively, while the dividend growth negatively. All three effects contribute to a stronger response of growth stocks to monetary policy. This effect is illustrated in Figure 7, which shows the return of zero-coupon equities after a monetary policy surprise.[10] Prices decrease after a tightening surprise, whereas expected returns increase, and dividend growth decreases. Furthermore, a tightening surprise will increase expected returns of growth stocks more than value stocks. This raises the question whether monetary policy decreases the value premium. The answer in this model is no. To understand that, first notice that the expectation of monetary policy surprise is zero. Hence, high frequency log returns will be on

[10] Golez and Matthies (2022) investigate the effects of monetary policy on the term structure of equity using dividend strips. In line with this model, they find that the long maturity assets fall more than short-term assets. However, they also find that short-term assets increase following a tightening surprise due to central bank information effects.

Figure 6: Model-implied portfolio responses to monetary policy



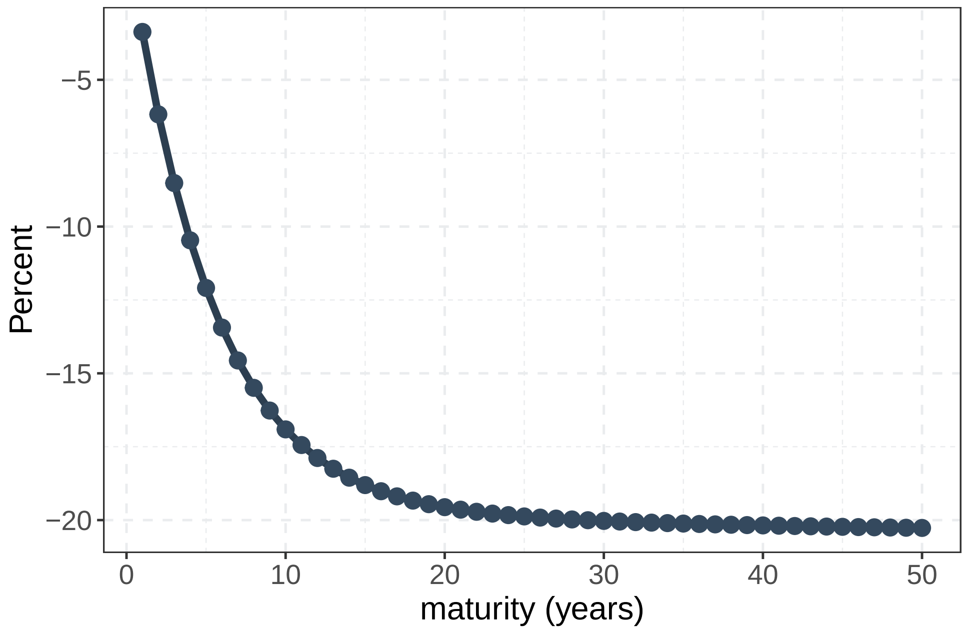
The figure shows the sensitivity of portfolio returns to monetary policy. Portfolios are constructed using 50.000 quarters of simulated data and constructing firms with a determinsitic share process. Firms are then sorted in portfolio deciles and their returns are regressed on high-frequency monetary policy surprises .

average zero. However, when computing the equity risk premium not only the expectation of log returns but also the variance of log returns matters because of Jensen's inequality. Hence, expected returns of high-frequency returns will be nonzero, although very small.

Table 9 confirms that the model generates higher expected returns for value stocks. Despite tighter monetary policy boosting the expected returns of growth stocks, the value premium remains positive and relatively unchanged. Additionally, the model produces an equity premium of 7% and a volatility of 18%, aligning with the empirical data. The model also mirrors empirical findings where estimated betas are lower for value portfolios, supporting the observation that the CAPM fails to account for the value premium.

All in all, this reduced form asset pricing model, which was created to explain the behaviour of growth and value stocks with basis on value premium, is in line with the responses of growth and value stocks to monetary policy, confirming that cash flow duration is enough to explain the impact of monetary policy on growth and value stocks.

Figure 7: Term structure of equity response to monetary policy



The figure shows the effects of monetary policy on the term structure of equity implied by the model. Zero coupon equity returns are simulated using 50.000 quarters of data. The zero coupon equity returns is then regressed on the high-frequency monetary policy surprise.

Table 9: Risk Premium of decile portfolios

	Value to Growth									
Portfolio	V	2	3	4	5	6	7	8	9	G
Panel A: Model										
$E(R^i - R^f)$	9.92	9.05	8.45	7.76	7.00	6.33	5.79	5.41	5.11	4.95
$\sigma(R^i - R^f)$	16.71	16.70	17.34	18.28	18.99	19.43	19.56	19.51	19.37	19.18
β_i	0.87	0.88	0.92	0.98	1.01	1.03	1.04	1.03	1.02	1.01
Panel B: Data										
$E(R^i - R^f)$	8.79	8.87	8.26	6.29	7.39	6.98	5.80	6.42	6.11	4.92
$\sigma(R^i - R^f)$	20.00	16.54	16.08	15.43	14.83	14.61	15.35	15.40	15.57	16.95
β_i	1.13	0.98	0.95	0.93	0.90	0.91	0.97	0.99	1.01	1.07

The table shows the risk premium, standard deviation and the betas of growth and value stocks implied by the model and estimated from the data. The moments in the model are estimated by simulating 50.000 quarters of data.

6.4 Economic channels of monetary policy effects on risk premium

Although I provide substantial evidence that the cash flow duration is the driving force of this heterogeneous response, duration is just the transmission mechanism through which shocks on risk premium spread to assets with different cash flow maturities. So far, my analysis is muted on why monetary policy should affect risk premium in the first place. There is, however, a vast amount of literature that supports this evidence. For example, my results on risk premium can be linked to the analysis of Gertler and Karadi (2015) for the credit market. Using a IV-VAR they show that the movements on credit costs following a monetary policy are mainly due to the reaction of both term premia and credit spreads.

My evidence that monetary policy affects stock returns through risk premium is also consistent with the risk-taking channel of monetary policy (Borio and Zhu, 2012), i.e. the fact that monetary policy affects financial markets and ultimately macroeconomic conditions by changing risk-taking and risk premia. There are different reasons why this channel takes place. For example, Bauer et al. (2023) provide evidence that those changes stem from the effects of monetary policy on the overall level of risk appetite. This is in line with the model from Lettau and Wachter (2011), as the risk appetite is commonly defined as the inverse of the price of risk. This is turn can be a product of several economic reasons. For example, Pflueger and Rinaldi (2022) incorporates the external habits model from Campbell and Cochrane (1999) in a New Keynesian model and show that a monetary policy tightening results in an increase in marginal utility. This, in turn, brings consumption closer to the habit level and increases risk aversion. There are other reasons for the effects of monetary policy on risk appetite, such as "flights to safety", risk limits of financial intermediaries, and "reach for yield" (Bauer et al., 2023).

7 Conclusion

This paper provides substantial new evidence of monetary policy channels to stock returns. Growth firms 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.

A more in-depth analysis suggests that the duration of cash flows is mainly responsible for the heightened sensitivity of growth stocks, challenging previous beliefs that exposure to financial frictions was the most important driver. Financial constraints explain a significant portion of cross-section stock return responses to monetary policy, but they are not related to market-to-book equity and monetary policy jointly.

The influence of duration on the response of growth and value stocks is further evidenced through a Campbell and Shiller decomposition. My analysis highlights that growth stocks are more reactive to monetary policy surprises, primarily due to more significant revisions in their discount rates. I show that this result arises because of the better predictability of future excess returns of growth stocks by the dividend yields, consistent with them having higher cash flow duration.

My findings are supported by the model proposed by Lettau and Wachter (2011), in which firms differ only by the timing of the cash flow payment. The model successfully replicates the observed policy sensitivity of growth and value stocks, while also preserving the value premium. All in all, my findings points to duration as the key determinant of the differing sensitivities of growth and value stocks to monetary policy. These results highlight the necessity for policymakers to closely consider the role of duration when evaluating the effects of monetary policy on the stock market.

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.[11]. 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

[11] 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. Specially 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 $t = 1, 2, .., T$:

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

where r denotes returns, mps 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:

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

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

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.

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 an 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.

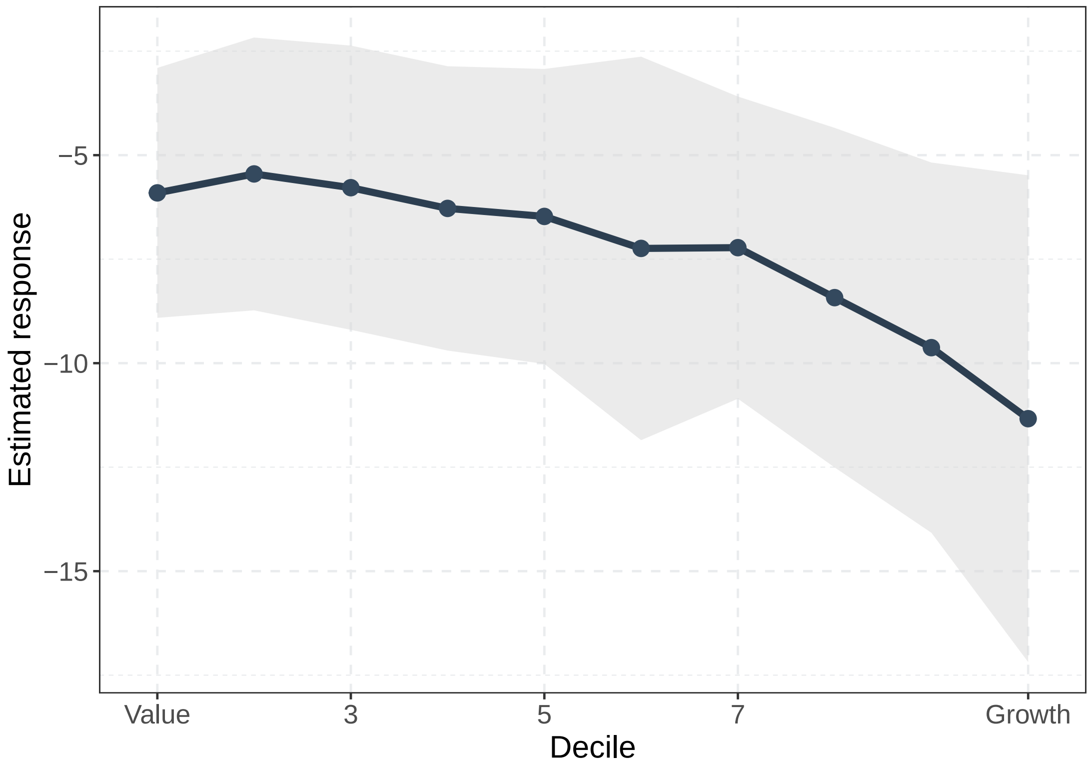
C Further empirical results

Table C.1: Reaction of stock returns to monetary policy surprises and market-to-book equity

	(1)	(2)	(3)	(4)	(5)	(6)
mb	0.002	−0.01	0.002	−0.02*	−0.01*	−0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
mps	−5.64**		−4.94**		−4.29*	
	(2.53)		(2.08)		(2.25)	
size	−0.005	−0.09**				
	(0.02)	(0.04)				
leverage	−0.05	0.01				
	(0.09)	(0.11)				
profitability	−1.94**	−1.14				
	(0.93)	(0.71)				
zlb			0.16			
			(0.22)			
dotcom					0.09	
					(0.11)	
mb*mps	−1.00***	−0.89***	−0.97***	−0.89***	−1.02***	−0.92***
	(0.31)	(0.26)	(0.35)	(0.29)	(0.37)	(0.27)
mps*size	−1.10**	−0.94***				
	(0.52)	(0.24)				
mps*leverage	7.85*	8.42**				
	(4.02)	(3.62)				
mps*profitability	11.33	2.63				
	(26.49)	(24.12)				
mb*zlb			−0.01	0.003		
			(0.02)	(0.01)		
mps*zlb			−6.27			
			(15.90)			
mb*mps*zlb			0.18			
			(0.99)			
mb*dotcom					0.05*	0.02
					(0.03)	(0.02)
mps*dotcom					−5.51**	
					(2.67)	
mb*mps*dotcom					0.08	
					(0.62)	
Constant	0.32***		0.21***		0.25***	
	(0.08)		(0.06)		(0.07)	
N	460,367	460,367	512,741	512,741	512,741	512,741
R^2	0.004	0.44	0.005	0.19	0.01	0.19
FE	NO	YES	NO	YES	NO	YES

The table shows the regression results of firm-level one-day returns on monetary policy, market-to-book equity, and further controls from January 1990 to December 2018. mps stands for monetary policy surprise, mb for market-to-book equity, zlb is a dummy for the zero lower bound, and dotcom a dummy for the period commonly referred to as dotcom bubble. Other controls are size (log of total assets), leverage (total debt divided by total assets), and profitability (operating income before depreciation, expressed as a fraction of total assets). Two-way clustered standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

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.2: 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.3: Robustness results for panel regressions on financial constraints

	(1)	(2)	(3)	(4)
mb		-0.01		-0.02^{*}
		(0.01)		(0.01)
mb*mps		-0.74^{***}		-0.87^{***}
		(0.24)		(0.29)
FC_{kz}	0.01	0.01		
	(0.04)	(0.04)		
FC_{kz}*mps	-1.56^{**}	-1.36^{**}		
	(0.64)	(0.64)		
FC_{sa}			0.01	0.01
			(0.03)	(0.03)
FC_{sa}*mps			-1.54^{**}	-1.14
			(0.66)	(0.74)
N	160,410	160,410	512,761	512,761
R^2	0.16	0.16	0.19	0.19

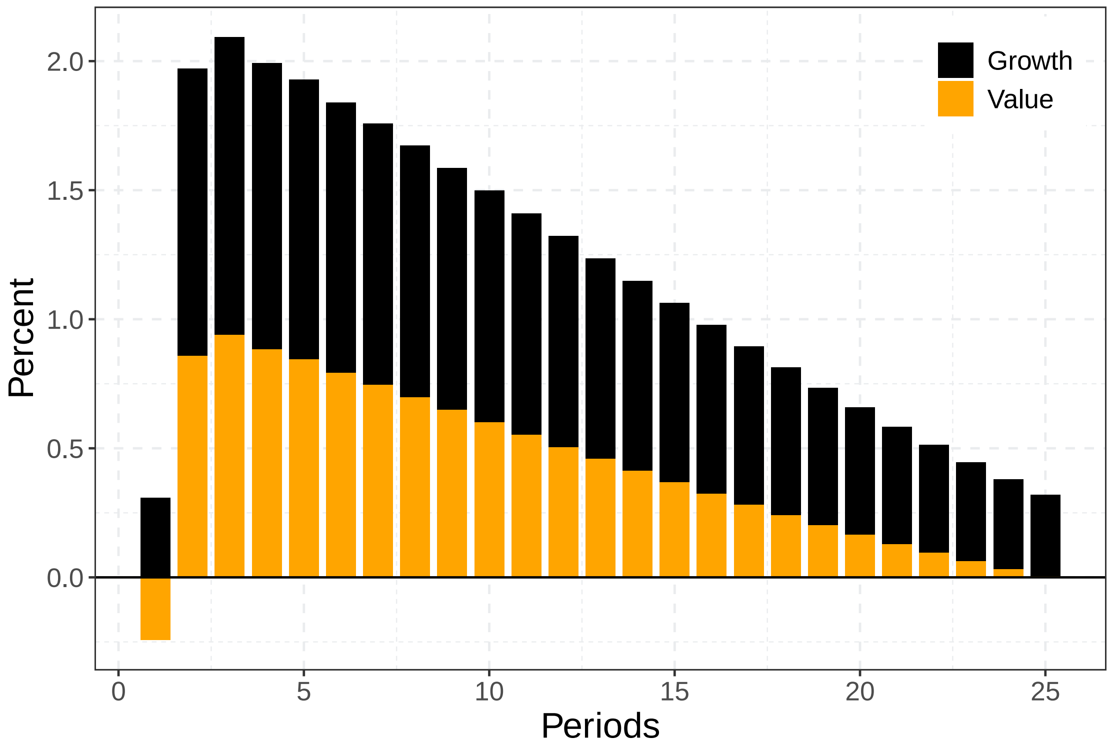
The table estimates the regression of returns on market-to-book equity, monetary policy, and financial constraints. Financial constraint index are measure using the KZ-index from Kaplan and Zingales (1997) and the SA-index from Hadlock and Pierce (2010). The observations go from January 1990 to December 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.

Table C.4: Summary Statistics VAR variables

	Variable	RR	DRF	R-Bill	SPREAD	DP	EX
	mean	0.10	0.00	-0.12	0.01	-3.73	0.69
S&P500	sd	0.36	0.06	1.06	0.01	0.41	4.30
	max	2.00	0.35	4.61	0.03	-2.77	12.38
	min	-0.95	-0.45	-4.22	-0.03	-4.5	-24.54
	mean	0.01	0.00	-0.06	0.01	-3.71	0.54
Russel Value	sd	0.37	0.03	0.69	0.01	0.17	4.23
	max	2.00	0.10	1.46	0.03	-2.93	11.34
	min	-0.95	-0.16	-2.66	0.00	-4.02	-19.27
	mean	0.01	0.00	-0.06	0.01	-4.47	0.62
Russel Growth	sd	0.37	0.03	0.69	0.01	0.38	4.89
	max	2.00	0.1	1.46	0.03	-3.83	11.89
	min	-0.95	-0.16	-2.66	0.00	-5.88	-19.45

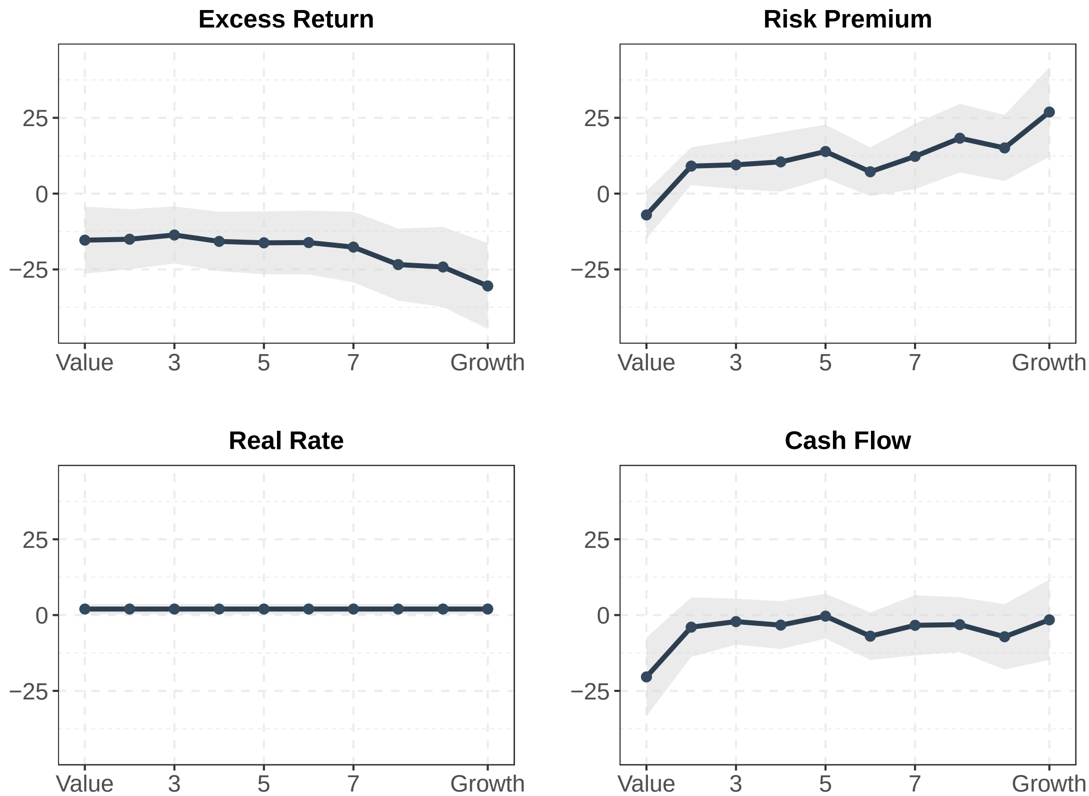
The table shows the summary statistics of the variables used in the first-order VAR: The real interest rate (RR), change in the 3-month bill rate (DRF), the relative bill rate (R-Bill), the spread between the 10-year and 1-month Treasury yield (SPREAD), the log of dividend price ratio (DP) and excess return (EX). The sample goes from Jan-1980 to Dec-2018 for the S&P 500 indexand from Jan-1995 to Dec-2018 for the Russel indexes.

Figure C.2: Impulse response of excess returns



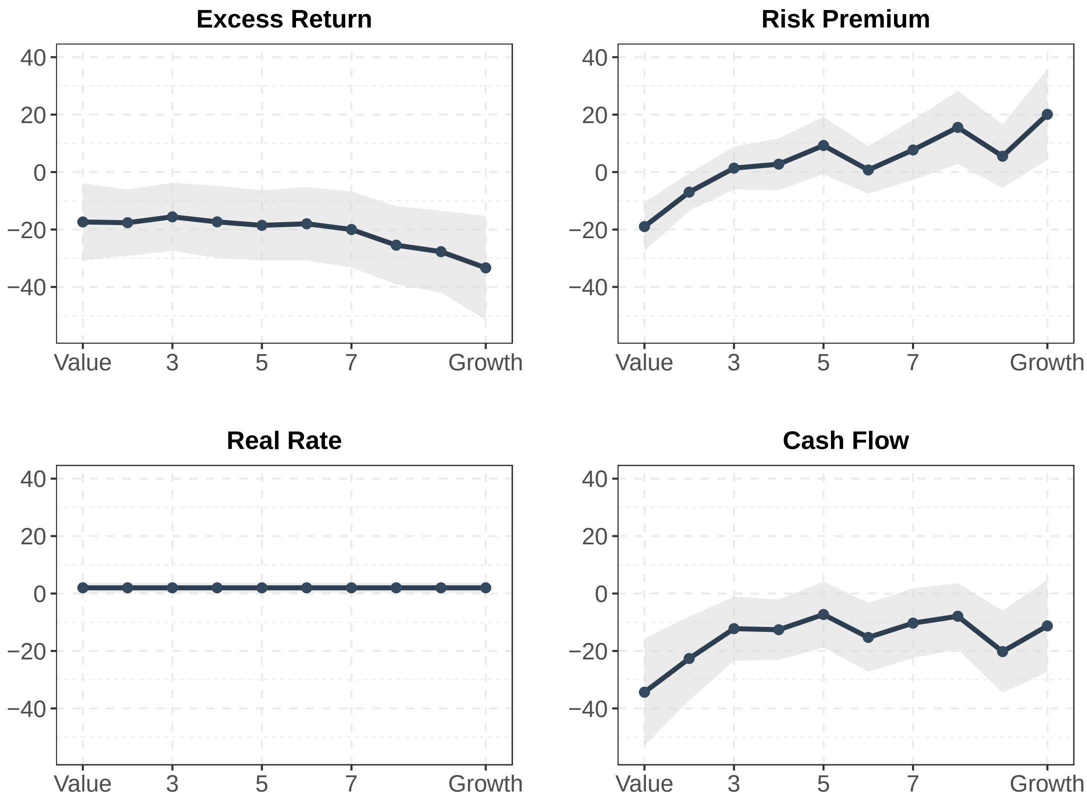
The figure shows the impulse responses of the excess returns from Russel growth and value stocks after a monetary policy surprise up to 25 periods ahead. The contemporaneous effect is omitted for illustrative purposes. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative 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-1990 to Dec-2018. Coefficients are estimated in two-steps.

Figure C.3: Response of unexpected excess returns to policy surprises using Fama and French with different ρ



The figure shows the reaction of the news components of the unexpected excess returns for 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-1980 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.

Figure C.4: Response of unexpected excess returns to policy surprises using Fama and French using Dividend Growth



The figure shows the reaction of the news components of the unexpected excess returns for 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-1980 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.

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