How differences in valuations impact stock market responses 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. Furthermore, I tackle the underlying economic sources of this disparity. The results indicate that monetary policy triggers stronger revisions of future discount rates for growth stocks and stronger cash-flow revisions for value stocks.

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JEL Classifications: E44, E52, E58

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1 Introduction

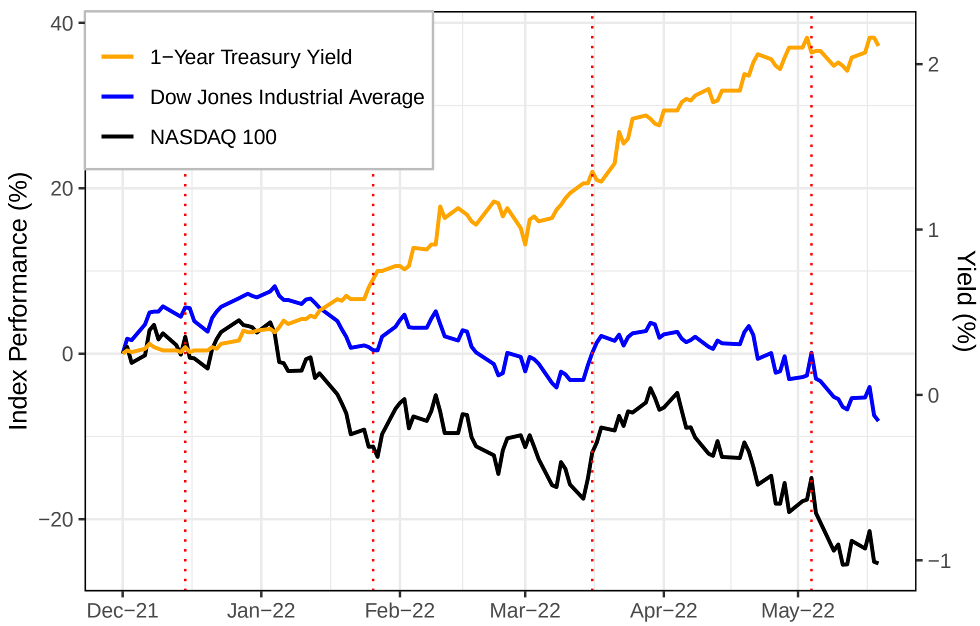
The macro-finance literature has provided conflicting evidence on the way stock returns with distinct valuation ratios respond to monetary policy. However, financial market experts frequently express clear-cut opinions on these responses. For example, they have argued that the underperformance of the NASDAQ relative to other stock indexes in the beginning of 2022 was due to the tightening of U.S. monetary policy.

Figure 1 illustrates the path of the Dow Jones Industrial Average (DJIA), NASDAQ and the 1-year treasury yield since the end of 2021. In this period, which is characterized by four FOMC announcements, the stock market correlates negatively with the 1-year treasury yield. The underperformance of the NASDAQ relativ to DJIA amounts to around -15%. The reasoning, according to industry experts, is that technology growth stocks — stocks with high price to fundamental ratio — are higher duration assets, i.e., growth stocks have cash flows further away in the future. Indeed, during the period shown in Figure 1 the NASDAQ has a price-to-book ratio of 5.7 compared to 4.6 of the DJIA. Nevertheless, Figure 1 does not provide causal evidence of monetary policy on stock returns, since other factors could have driven the stock prices and the yields.

This paper uses a high-frequency approach to provide new evidence that growth stocks exhibit a greater sensitivity to monetary policy than value stocks. The estimated difference is statistically and economically significant. For example, a change of one standard deviation in market-to-book equity corresponds to an approximate 2.2 percentage points change in returns following a monetary policy tightening. This difference in response is observed at the index level, individual stock level, and across portfolio sorts, suggesting that this result does not disappear due to idiosyncratic noise or diversification. The higher response of growth stocks is found for portfolios with valuation ratios (in the form of market-to-book equity) close to the market average, as well as for extremely high or low valuation ratios, i.e., it is not caused solely by a small number of stocks. After a monetary policy surprise a significant larger response of growth stock relative to value stocks will persist on average for several days. Yet, a monthly analysis is not well suited to capture these causal effects, which is one of the reasons previous studies have failed to find the same result.

While the duration argument is widely accepted among industry professionals, it has yet to be investigated in academic studies of the stock market's response to monetary policy. Previous studies have instead focused on the impact of monetary policy on firms through the lens of fundamentals. For example, Maio (2014) argues that value stocks should respond stronger to monetary policy, because of the credit channel mechanism through which monetary policy transmissions to investment operates. The balance sheet channel states that after a monetary policy easing, firm's net worth increases due to a higher collateral value. The bank lending channel operates through the fact that banks increase their loan supplies after a monetary policy easing providing firms with more access to loans. Both channels enable firms to increase investment, and ultimately future cash flows. Yet, these explanations imply that monetary policy impacts firms differently depending on their vulnerability to external funds. Specifically, as Ehrmann and Fratzscher (2004) explain, the stock price of firms with larger informational asymmetries should react more to monetary policy, as they will find it harder to access external funding.

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.

Stock prices move, because investors' future expected real rates, discount rates, or dividends have changed. Consequently, the price of a stock will respond to monetary policy surprises, because they trigger the revision of these three components. However, since the effects of these components on the stock prices may offset or amplify one another, identifying the source of the greater response of growth stocks is not a simple task. For instance, if monetary policy triggers a stronger revision of future expected returns for growth stocks and a stronger revision of expected cash flows for value stocks, determining which stock exhibits a greater response depends on which revision dominates.

To clarify this, I use a Campbell-Shiller decomposition to break down the unexpected returns in cash flow, discount rates and real rates news. The goal is to show the extend to which each component reacts to monetary policy and whether these reactions depend on valuation ratios. Bernanke and Kuttner (2005) use the same approach to infer which news are mainly affected by monetary policy on an aggregate level. Thus, this paper can be seen as an extension to the cross-section of stock returns. This analysis helps understanding the effects of monetary policy in three different ways: First, it confirms that real rates play a relatively minor role when it comes to affects of policy surprises on stock returns. Second, it underlines the importance of discount rate news as driving force of growth stock prices relative to value stocks. Third, on the aggregate level value stocks have a higher exposure to cash flow news, but this exposure is not enough to counteract the discount rate effects.

Related Literature

The duration argument has little empirical support in the macro-finance literature, which is full of conflicting evidence. 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. Another argument is that a value firm is more likely to be financially constrained, because lenders will be willing to lend less to them given their poor future financial prospects.

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." However, Ehrmann and Fratzscher (2004) acknowledge that the relationship between financial constraints and Tobin's q is ambiguous, because a firm with a high q may also be less financially constrained as a consequence of a relatively high value of its assets. Their empirical results speak in favour of the first explanation.

To interpret the results from Maio (2014) and Ehrmann and Fratzscher (2004), which are the two reference points in this study, their limitations need to be addressed. Ehrmann and Fratzscher (2004) use a relatively low sample of 79 FOMC meetings. Their sample is composed only of S&P500 firms, which can lead to survival bias. For example, if value stocks are more distressed and distressed firms have a relatively lower response to monetary policy due to lower liquidity, the response of value stocks will be overestimated, because only established value stocks (that made into the S&P500) will be considered. 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 as well.

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

More recently, new empirical studies of the effects of monetary policy surprises on the cross-section of returns have gained more attention. For example, Ippolito et al. (2018) show that differences in bank loan leverage among companies contributes to stock price response to monetary policy surprises, but that this contribution broke down during the zero lower bound. Gürkaynak et al. (2022) find that stock returns of firms with high debt floating rate exposure react stronger to forward guidance shocks, but that this effect is mitigated if firms hedge their interest rates risk. The firm-level analysis in this paper is similar to these two studies. I construct my sample in a similar fashion as Gürkaynak et al. (2022) and use fixed effects to avoid unobserved effects.

To understand the stock price movements, I build up on the ideas of Campbell and Shiller (1988), Campbell and Ammer (1993) and Vuolteenaho (2002). Campbell and Ammer (1993) combine the linear-approximation of the stock price identity derived by Campbell and Shiller (1988) with a VAR to decompose unexpected return movements in discount rate and cash flow news. Vuolteenaho (2002) applies the same logic to the cross-section of stocks. He finds that single stock returns are mainly driven by cash-flow news, but that cash-flow news are diversified away in aggregate portfolios. Contrarily, discount rate news are strongly positive correlated. Bernanke and Kuttner (2005) further decompose returns into real rates, expected discount rate and cash flows news in the context of high-frequency monetary policy. They find that monetary policy affects stock prices mainly through future discount rate and cash flow and less through real rates.

[1] While it could be argued that Compustat data is also affected by survival bias, the bias should be weaker than just restricting the sample to the S&P500. In addition, Davis (1996) shows that the survival bias in Compustat does not change the coefficients of the models.

2 Data and Summary Statistics

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

2.1 High-frequency data for FOMC announcements

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

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

2.2 Firm-level Data

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

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

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

2.3 Aggregate Data

To investigate the effects of policy surprises on aggregate measures of valuation and stock returns, I extract daily prices for the S&P500, the Russel 1000 and the Russel Growth and Value Index as well as the corresponding quarterly aggregate multiples from Bloomberg. Table 1 shows the summary statistics of the four stock indexes.

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 and valuation multiples for the fourth stock market indexes. The sample goes from January 1990 to December 2018.

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

3 One-day Analysis

3.1 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. Yet, their surprise measure does not account for forward guidance.

To analyse the policy surprise effects on aggregate growth and value stocks, I use the Russel Value and Growth 1000 Indexes. The last two columns of Table 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 about 12 percentage points after a one percentage point increase in monetary policy surprises, 4 percentage points more than the Russel Value Index. However, the difference in response of the one-day return is not statistically significantly different from zero.

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

To evaluate the effects of the aggregate valuation, I regress the one-day returns on valuations interacted with monetary policy surprises, where valuations are measure by market-to-book equity and price-earnings ratio. Table 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 returns to monetary policy surprises and market-to-book equity

Panel A	S&P500 (Jan-90 - Dec-18)	Russel 1000 (Jan-90 - Dec-18)	Russel Value (Jan-91 - Dec-18)	Russel Growth (Jan-91 - Dec-18)	Growth - Value (Jan-91 - Dec-18)
mps	-9.54^{***}	-9.58^{***}	-7.71^{***}	-11.98^{***}	-4.27
	(2.42)	(2.45)	(2.37)	(3.34)	(2.73)
Constant	0.21^{***}	0.21^{***}	0.22^{***}	0.24^{***}	0.02
	(0.07)	(0.07)	(0.07)	(0.08)	(0.04)
N	259	259	248	248	248
R^2	0.11	0.11	0.08	0.14	0.05

Panel B	S&P500		Russel 1000	
mps	-8.78^{***}	-8.56^{***}	-10.90^{***}	-10.30^{***}
	(2.31)	(2.48)	(2.94)	(3.41)
mb*mps	-2.18		0.03	
	(1.80)		(2.36)	
pe*mps		-2.61		-1.33
		(2.20)		(3.06)
Observations	256	256	201	201
R-squared	0.12	0.12	0.12	0.13

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

3.2 Panel regressions

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

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

where i denotes the firm, t the day of the FOMC announcement, r the stock return, mps

the monetary policy surprise, mb the market-to-book equity, and γ and α the fixed effects. In Appendix B I provide the theory necessary to understand how our regression design avoids the problems of unobserved effects.

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

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

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

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

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

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

3.3 Portfolio-level Results

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

I group the firms into 10 equal-size portfolios sorted by their lagged market-to-book equity for each quarter in the sample. Table 4 presents the summary statistics of market-to-book equity for each portfolio. Although it would seem obvious to expect a monotonically increasing maximum market-to-book ratio, the maximum value of the first portfolio is, in fact, larger than the maximum from the second portfolio. This is because, in most cases, stocks with negative book equity are assigned to the first decile. Thus, the aggregate book value in the first decile is reduced by the negative book equity, in which case the overall market-to-book value increases. The standard deviation from the last decile is notably larger than in the others, indicating that a lot of the noise in the data comes from this extreme decile.

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

Table 4: Summary Statistics of Market-to-Book Equity sorted Portfolios

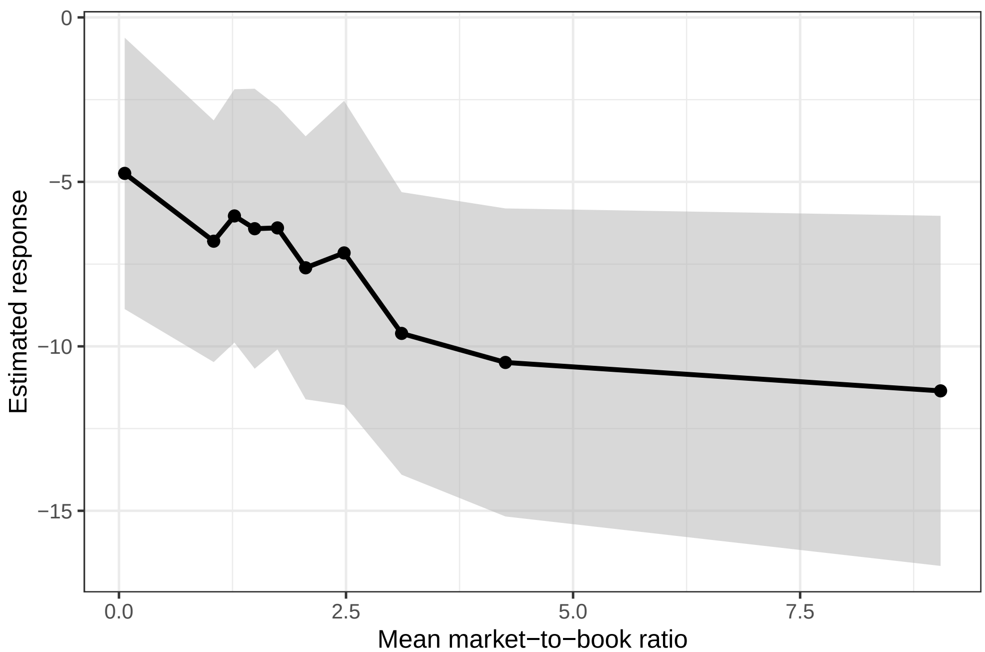
Portfolio	Mean	SD	Max	Min
1	0.93	0.29	2.1	0.34
2	1.04	0.19	1.46	0.57
3	1.27	0.21	1.78	0.71
4	1.49	0.23	2.1	0.87
5	1.75	0.26	2.38	1.05
6	2.06	0.31	2.79	1.26
7	2.48	0.38	3.25	1.52
8	3.12	0.5	4.51	1.91
9	4.23	0.83	6.82	2.67
10	7.83	2.07	13.6	4.88
Overall	2.57	0.61	4.31	1.59

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

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

Table 5 shows the regression of the spread portfolios on monetary policy surprises. Columns (1) to (3) show that the 10%, 30% and 50% spread portfolios are in line with the panel regressions: The portfolios with relatively higher average market-to-book equity drop significantly more after a monetary policy tightening surprise. The last two columns demonstrate that the results are not solely driven by a small extreme sample. A portfolio with stocks in the highest 10% spectrum of market-to-book equity (the stocks which are the closest to the growth extremity) react significantly stronger than all others. Likewise, a portfolio with stocks in the lowest 10% spectrum of market-to-book equity (the stocks which are the closest to the value extremity) react significantly less to monetary policy surprises.

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



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

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

The fact that the first and last decile portfolios do not seem to be statistically different in Figure 2, but are indeed significant when running the regression in Table 5, might be puzzling. I point out that it is not possible to infer from Figure 2 whether the two portfolios are statistically significantly different. Because the figure does not take into account the correlation between the estimated coefficients, a high correlation can lead to smaller standard errors which makes the results in Table 5 significant.

Table 5: Reaction of spread portfolios to monetary policy surprises

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

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

4 Results Based on Multiple Days

4.1 Monthly Analysis: Reconciling with Maio (2014)

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

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

To revisit the results obtained by Maio (2014), I regress 10%, 20%, and 30% spread portfolios on the first difference of the federal funds rates.[3] Panel A from Table 6 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

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

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: Reaction of monthly spread portfolios to federal funds rates

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

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

Table 7 repeats the regressions from Table 6 using the exogenous monetary policy surprises. The policy surprises are aggregated by summing all surprises within a month. In case of no FOMC announcement within a month, the policy surprise is zero. I find negative, but insignificant effects of policy surprises on the spread portfolio returns. The most plausible explanation for these results is the increase in the noise, which is indicated by the very low R-squared.

Table 7: Reaction of monthly spread portfolios to monetary policy surprises

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

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

4.2 Dynamic responses of stock returns to policy surprises

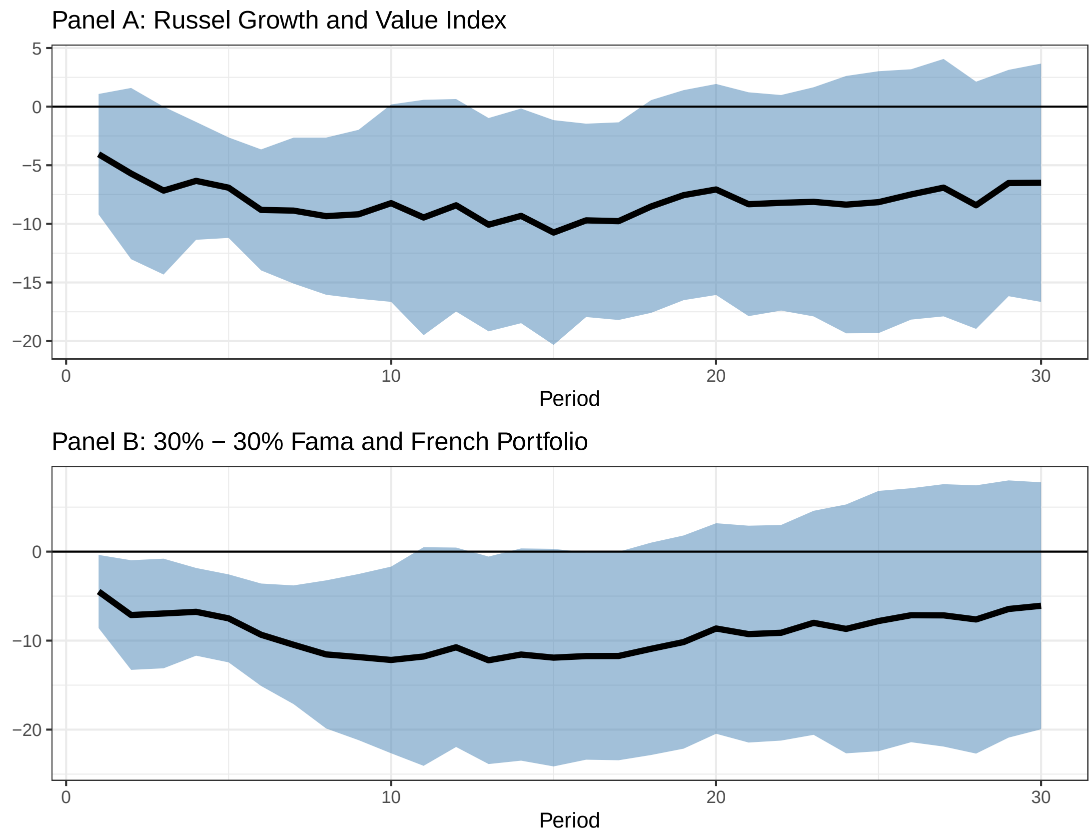
The analysis with the monthly frequency raises the question how long do the different policy responses of stock returns last for. To answer this question I regress the spread returns k-days ahead of the FOMC announcement on the policy surprise:

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

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 on the fact that, at the beginning, the policy response decreases with time and reaches 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.

5 Policy surprises and stock price decomposition

The overwhelming evidence of the stronger response of growth stocks to monetary policy raises the question of what factors explains this superior response. As previously mentioned, financial experts usually interpret the stronger reaction of growth stocks with the fact that growth stocks are longer duration assets. The duration measure is commonly used in the fixed income market and assess the sensitivity of prices of fixed income instruments to parallel shifts in the yield curve. However, because the yield curve does not respond to monetary policy surprises with parallel shifts (see, for example, Gürkaynak et al. (2005)), it is not the case that long-term bonds react more to monetary policy than short-term bonds. Given this insight, why should this be any different for the equity market?

The standard approach to explain stock price movements is the decomposition of Campbell and Shiller (1988). This method breaks down the price movements in revisions of future expected real rates, discount rates, and cash flows. Using the decomposition will help to identify the channel through which the superior response of growth stocks arises. If the future discount rates of growth stocks are revised more strongly to policy surprises, the duration may be the key factor in explaining these responses. However, revisions of future cash flows may also play a significant role and, in case value stocks are more financially constrained, dampen the superior responses of growth stocks.

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

5.1 Decomposing stock returns

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

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

where

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

d is the log-dividend, r the real rate and y the excess return. The log-linearization introduces ρ, which is the steady-state ratio of the equity price to the price plus dividend.

Following Campbell and Ammer (1993) I set it to 0.9962.

Given identity 1 the variance decomposition of unexpected equity returns can be determined:

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

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

$$z_{t+1} = Az_t + \varepsilon_{t+1} \tag{3}$$

Equation 3 enables to back up the news on expected excess returns, real rates, and current expected returns:

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

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

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

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

Table 8 shows the variance decomposition of excess returns (calculated with equation 2). As the price-dividend ratios of the Russel Index go back only to 1995, I extrapolate the data using the fitted value of a regression of the price-dividend ratio of the S&P500 on the price-dividend ratio of both Russel indexes. In this way the sample starts in 1979. As previously documented, the variance of S&P500 returns is mainly explained by the variance of cash-flow news, future excess returns news and their covariance. The variance of future dividends has the largest share.

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

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

Table 8: Variance Decomposition of Excess Equity Returns

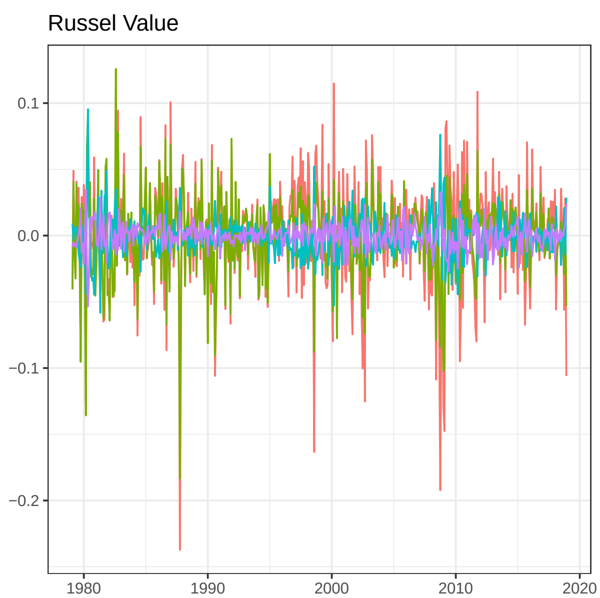
	S&P500		Russel Value		Russel Growth	
	Total	Share (%)	Total	Share (%)	Total	Share (%)
var(excess return)	18.50		17.46		23.78	
var(dividends)	7.36	39.76	9.69	55.50*	13.54	56.95**
		(25.62)		(31.72)		(25.84)
var(future returns)	2.78	15.01	2.42	13.86	20.93	88.01
		(22.36)		(17.46)		(90.18)
var(real rates)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

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

Apart from the understatement of the expected returns predictability, revisions of future excess returns could be indeed more volatile for growth stocks than for value stocks. Figure 4 shows the time-series of unexpected returns from Russel Growth and Value Indexes as well as its three components. The volatility of future excess returns changes over time and peaks during the period of the dotcom crisis, implying very large future excess returns revisions during this period. This is plausible, since the crisis affected especially prices from technology growth firms (taking out the year 2000 from the sample leads to a lower share of future excess returns variance and a negative correlation of future excess returns and dividends).

Last, I discuss the positive correlation between future dividends and excess returns. Negative forecast errors should stem from upwards revisions of future expected returns and/or downwards revisions of future expected dividends. Thus, why are future expected returns and dividends positively correlated?

Figure 4: Excess Returns News Decomposition



The figure shows the path of the unexpected excess returns (ERM), news on future expected cash flow (NCF), news on future expected discount rate (NDR) and news on future expected risk-free rate (NR). The sample goes from Jan-1979 to Dec-2018.

The reason seems to lie on the period of the dotcom crisis as well. When revisions to future discount rates move in magnitude more than the unexpected returns, revisions to cash flows need to move in the opposite direction to counteract the revisions to future discount rate (assuming revisions to real rates are very low and almost insignificant). This argument becomes clear with a quantitative example: Assume, for example, that unexpected returns are 5 percentage points on a given day and that revisions to real rates are 0. Perhaps, the 5 percentage points stem from a downwards revision of future excess returns of 3 percentage points, which pins down a 2 percentage point movement related to revisions on cash flows, since they are residuals. This decomposition is plausible, because downwards revisions to future expected returns increase prices and upward revisions to future cash flows increase prices as well. Yet, in a different scenario (for example due to the dotcom crisis) the model estimates a downward revision of future expected returns of 10. In this case revision of future cash flows needs to be -5, i.e., the model forces a downward revisions of future cash flows to be in line with an increase in prices. Campbell and Ammer (1993) also find a positive correlation between future excess returns and dividends for their sample from 73:1 and 87:2. The variance of future excess returns makes up in that sample more than 100% of the variation in unexpected returns (See Campbell and Ammer (1993), Table III).

5.2 Effects of monetary policy on aggregated news

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

$$z_{t+1} = Az_t + \Phi mps_{t+1} + \nu_{t+1} \tag{4}$$

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

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

Since the VAR specification requires a steady frequency, the model is estimated in a monthly frequency. Table 9 shows the estimated responses of the S&P500, Russel Value

Index and Growth Index. The results for the S&P500 favour cash-flows news as the main component affected by monetary policy, i.e., price movements in the stock market caused by monetary policy arise mainly, because investors revise their expectation of future cash flows. This outcome resembles Bernanke and Kuttner (2005), even though their policy surprise is different.

The transmissions of monetary policy to value and growth stocks differ considerably. Monetary policy affects prices of growth stock mainly through revisions of future excess returns whereas they affect value stocks (similarly to the aggregate market) through revisions of future dividends.

Table 9: Breakdown of monetary policy effects on unexpected excess returns

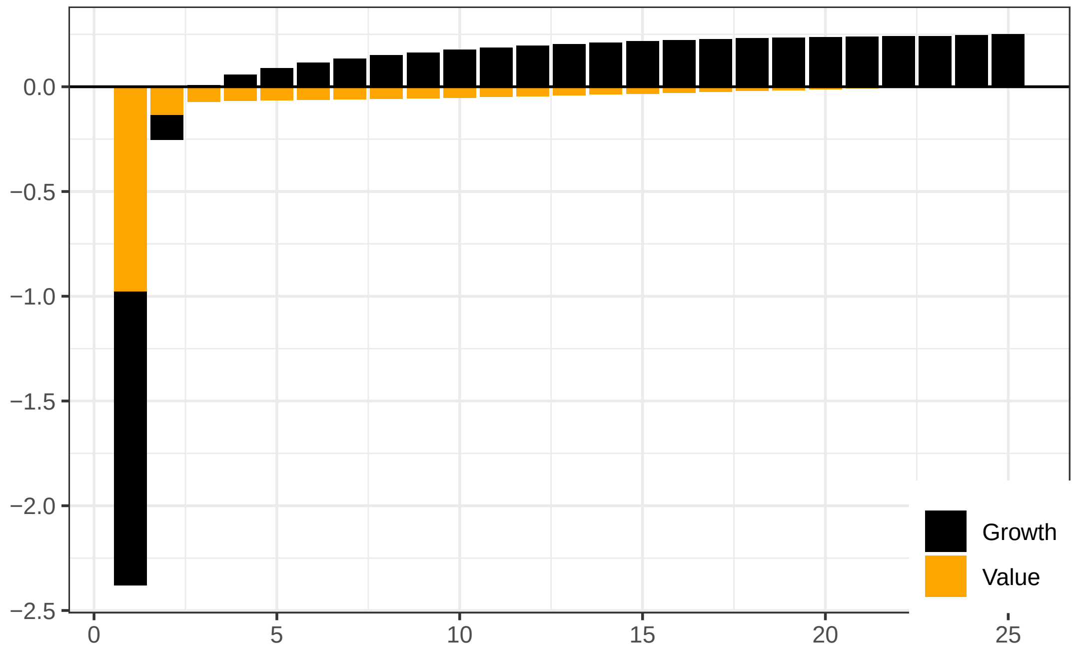
	S&P500	Russel Value	Russel Growth
Current excess return	-16.86***	-14.08***	-21.34***
	(5.34)	(5.34)	(6.18)
Future excess returns	1.38	1.70	18.74***
	(2.99)	(2.95)	(6.29)
Real interest rate	2.77**	3.55***	2.83**
	(1.26)	(1.35)	(1.21)
Dividends	-12.71***	-8.83**	0.23
	(3.64)	(4.31)	(5.25)

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

Table 9 confirms that revisions of future dividends are more reactive to monetary policy for value stocks. This supports Maio (2014)'s arguments that value stocks are more financially constrained and that after a policy surprise, financially constrained firms see their stock prices move more. Revisions on real rates are stronger for value stocks. This is not surprising, since movements in the short-term real rate will have a stronger impact on prices of firms with short-term cash flows.

To gain a better understanding of why revisions of future discount rates are stronger for growth stocks, Figure 9 plots the impulse response of the excess return regression. The figure helps to see the difference in the long-run forecastability in excess returns. The reaction of value excess returns is minor after one year (and negative) whereas the response of growth stocks is positive and relatively big even after 25 months. Discounting these responses to the present and summing them up yields a big positive reaction of future discount rates.

Figure 5: Impulse response of excess returns

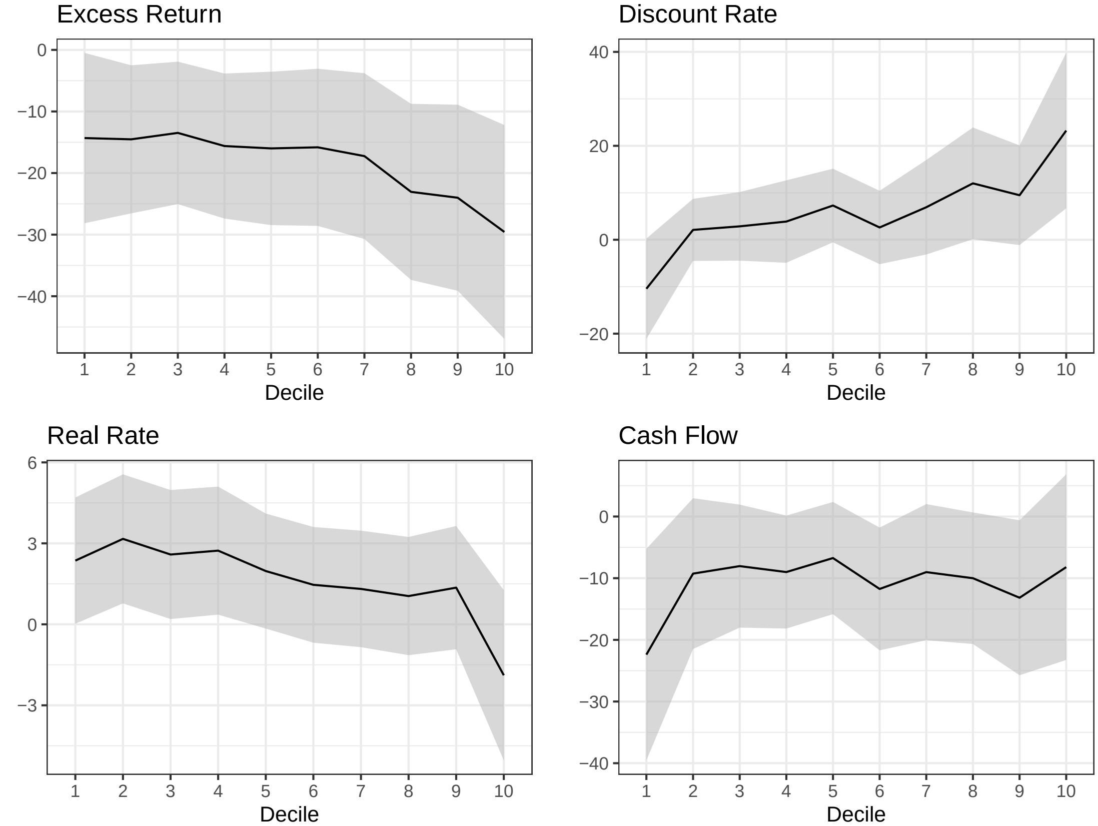


The figure shows the impulse responses of the excess returns from Russel growth and value stocks after a monetary policy surprise up to 25 periods ahead. The contemporaneous effect is omitted for illustrative purposes. I estimate a VAR(1) with the excess equity return, the real interest rate, the relative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

5.3 Decomposition of Fama and French portfolios

In this section I repeat the Campbell and Ammer decomposition for Fama and French portfolios sorted by market-to-book equity. The goal is to investigate the effects of policy surprises on a lower aggregation level. Figure 6 plots the responses of the unexpected excess returns and from its three components against the ten deciles.

Figure 6: Response of unexpected excess returns to policy surprises using Fama and French



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

The upper left figure shows that the response of the forecasting errors to monetary policy decreases with market-to-book equity, i.e., the revision of stock prices with relatively high market-to-book equity is larger. The magnitude of the response doubles from the first to the last decile. The discount rate news is typically positive and increases on the deciles, implying that the impact of monetary policy on revisions of discount rates are stronger growth stocks. Likewise, the revisions of future real rates are, with exception of the last decile, positive and decrease with increasing average market-to-book equity. Perhaps surprising is that the portfolio deciles paint a different picture, when it comes to the revisions on future cash flows. Given the outcome in Table 9 an increasing pattern of the impacts on cash flow news would be expected. Indeed, the cash flow revisions for the first portfolio is notably larger in magnitude, but this pattern does not continue for the other portfolios. Also all estimated responses are negative, which differs from the slightly positive coefficient estimated for the Growth Russel Index.

The estimated effects in Table 9 and Figure 6 indicate that growth and value stocks move for two different reasons: After a policy surprise investors revise their expectation of future cash flows and discount rates. The first has a stronger effect on prices of value stocks and the second on prices of growth stocks. The revisions of expected discount rates, which is the price sensitivity to discount rates, encompasses the duration of stock prices. Hence, the results can be interpreted as a confirmation of the duration argument. Yet, another reason why the effects on the revisions to discount rates are larger could be that the discount rates of growth stocks are more sensitive to monetary policy, i.e., the risk premium of growth stocks' investors moves stronger after a monetary policy surprise than the risk premium of value stocks' investors.

6 Conclusion

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

It is well-known that growth stocks are higher duration assets, yet remains unclear whether this is the determining factor for the superior response of growth stocks to monetary policy. To shed light on the origins of the superior response of growth stocks, I show using a Campbell-Ammer decomposition that growth stocks react more because investors revise their expected future discount rates more strongly for growth stock than for value stocks following a monetary policy surprise. This could be a consequence of the higher duration of growth stocks. As the results from the Russel Index indicate, revisions of expected cash flows seem to affect value stocks more, possibly because value firms are more financially constrained. Hence, growth stocks seem to react more because the superior revisions of future discount rates for growth stocks outweigh the superior revisions of future cash flows for value stocks.

It remains uncertain whether duration is the sole cause of the superior response of growth stocks to monetary policy. While it may be relevant, it is also possible that discount rates for growth stocks are more reactive to monetary policy surprises, for example, as a result of differing risk preferences. Perhaps a way to address this question is to decompose the revisions of future stock returns into a common and an idiosyncratic factor. If the common factor, which influences both growth and value stocks equally, is found to react strongly to monetary policy surprises, this would confirm that duration is the primary factor. Conversely, if the idiosyncratic factor is found to be more affected, this would suggest that discount rates for growth stocks are more reactive than those for value stocks.

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.[4]. 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

[4]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:

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

B Fixed Effects Specification

B.1 Omitted variable bias

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

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

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

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

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

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

Plugging it back in B.1 yields:

$$r_{i,t} = (\beta_0 + \gamma_0\delta_0) + (\beta_1 + \gamma_1\delta_0) \times mp_t + (\beta_2 + \gamma_0\delta_1) \times mb_{i,t} + \tag{B.3}$$
$$(\beta_3 + \gamma_1\delta_1) \times mb_{i,t} \times mp_t + \nu_t + \varepsilon_{i,t} \tag{B.4}$$

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

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

The Pooled OLS estimator is biased and inconsistent, if γ_1 and δ_1 are different from zero. Moreover, given that mb and valuations are likely positively correlated, the estimator of the effects of monetary policy on stock returns will be overestimated (Consistent with the results in table 3 later).

B.2 Correcting the bias with Fixed Effects

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

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

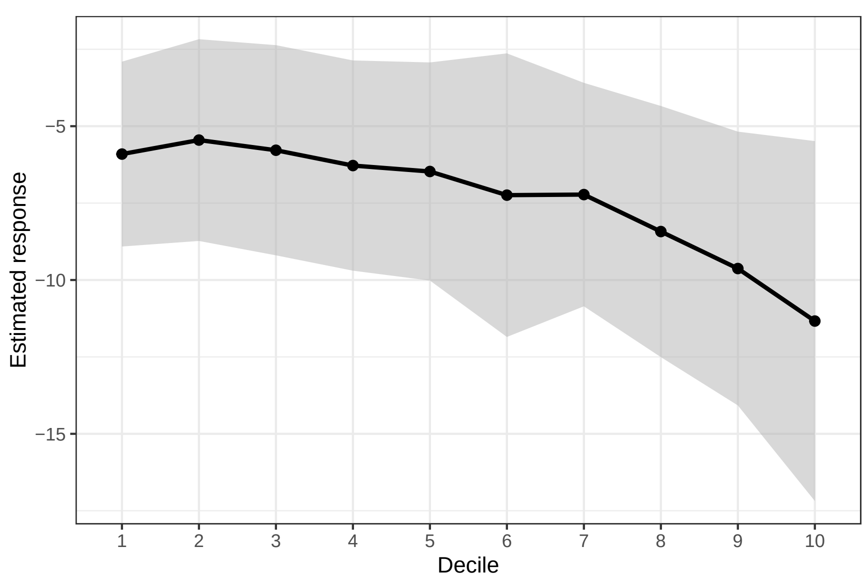
Where $\ddot{x}_{i,t} = x_{i,t} - \bar{x}_t$ and $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{i,t}$.

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

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

C Further empirical results

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



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

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

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

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

Table C.2: Summary Statistics VAR variables

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

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

Table C.3: Excess return regression on state variables

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

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

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