Another Look at the Stock Return Response to Monetary Policy Actions*

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Abstract. I analyze the effect of monetary policy actions on the cross-section of equity returns. Based on earlier theoretical work for the monetary transmission mechanism one can argue that changes in monetary policy should produce differentiated effects on firms and stocks with different characteristics. By using different portfolio sorts the results show that the impact of monthly changes in the Federal funds rate is greater for the returns of more financially constrained stocks (e.g., small and value stocks) than on the returns of stocks with a more favorable financial position (e.g., large and growth stocks). By using a VAR methodology, the results indicate that the negative effect of Fed funds rate shocks on stock returns comes from a corresponding negative effect on future expected cash flows (cash-flow news), which is stronger than the impact on future equity risk premia (discount rate news). Thus, cash-flow news is the main return component affected by changes in the Fed funds rate. These results are reasonably robust to different VAR specifications. Moreover, the dispersion in return responses to monetary shocks across stocks is explained by a similar dispersion in the effects into cash-flow news, which outweighs the dispersion in discount rate news betas. These results represent new evidence on the effect of monetary policy on stock prices and on the monetary transmission mechanism.

1. Introduction and Motivation

Monetary policy is one of the macroeconomic variables with the greatest impact on stock markets and the Federal Open Market Committee (FOMC)

decisions are closely followed by stock market participants.[1] Specifically, as documented in numerous empirical studies, monetary policy actions have a robust and significant impact on stock market returns (see, for instance, Jensen, Mercer, and Johnson, 1996; Patelis, 1997; Thorbecke, 1997; Ehrmann and Fratzscher, 2004; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Chen, 2007; and Maio (2012a), among others).[2] In particular, Thorbecke (1997), Ehrmann and Fratzscher (2004), Rigobon and Sack (2004), and Bernanke and Kuttner (2005) find a negative contemporaneous correlation between Fed policy tightening [e.g., rises in the Federal funds rate (FFR)] and excess market returns.

This article extends the existing analyzes by focusing on the effect of monetary policy actions on the cross-section of stock returns by using decile portfolios sorted on size, book-to-market ratio, earnings-to-price ratio, and cash flow-to-price ratio. The results document how the magnitude of the return response to monetary policy shocks varies across portfolios sorted on these characteristics. More importantly, the article decomposes the effect of changes in the Fed funds rate (ΔFFR) over equity portfolio returns into the fundamental components of excess stock returns—discount rate news, cash-flow news, and real interest rate news.

The main theoretical explanation for the impact of monetary policy actions on equity returns is the credit channel mechanism, as in Bernanke and Gertler (1989, 1990, 1995), Bernanke and Blinder (1992), Bernanke, Gertler, and Gilchrist (1994), Gertler and Gilchrist (1994), Kiyotaki and Moore (1997), among others. This mechanism works through a balance sheet channel, or alternatively a bank lending channel. In the balance sheet channel, an adverse monetary policy shock raises the information and agency costs associated with external finance, or reduces the value of the firms' assets that act as collateral for new loans. This results in reduced access to bank loans and external finance in general, forcing the firm to decrease its level of investment, and ultimately reduces cash flows and rates of return. In the bank lending channel, a contractionary monetary policy shock leads banks to simultaneously decrease the supply of loans and charge higher interest rates for new loan contracts, causing a decline in firms' cash flows, real earnings, and stock returns. Thus, in both channels, an adverse monetary policy action has a negative impact on firms cash flows.

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[1] For example, Fair (2002) finds that most of the large swings in stock prices have origins in monetary policy shocks.
[2] In related work, Wongswan (2006) and Ammer, Vega, and Wongswan (2010) find a significant impact of US monetary policy actions on international equity markets.

The two channels suggest that a rise in the Fed funds rate may have a differentiated impact on firms, depending on their vulnerability to external finance and hence, interest rate movements. Thus, more financially constrained firms should be more responsive to monetary policy actions than less constrained firms. Small capitalization stocks, as an example, should respond more intensely to contractionary monetary policy shocks than large caps. On the other hand, value stocks—that is, stocks with a high book-to-market ratio, earnings-to-price ratio, or high cash flow-to-price ratio—should respond more to monetary shocks than growth stocks (stocks with low book-to-market ratio), given that value stocks are more likely to be financially constrained (their low-equity valuations are a result of negative shocks in their past cash flows). The reasons are two-fold. First, small and credit-constrained firms are more vulnerable to increases in the information and agency costs of external finance that result from adverse monetary policy shocks. Their size and relatively low valuations all contribute to make them more dependent on the high-cost information gathering activities by banks and other financial intermediaries. Second, the cost of external finance is greater for these firms, making them more vulnerable to additional increases in borrowing costs or credit rationing.

Even if the negative impact on the cash flows of firms takes some time to materialize due to the monetary policy transmission lag, it is natural that rational forward-looking investors, who price stocks as the sum of discounted future cash flows, will immediately discount the relevant cash flows, causing a decline in equity prices and in current excess returns. This may occur even before the actual impact of contractionary monetary policy on firms' cash flows and earnings. This article might be viewed as a test on the relevance of the credit channel mechanism. By analyzing in detail the return reaction on stocks of firms with different characteristics and financial constraints, one might be able to assess the plausibility of the theoretical propositions.

Similarly to Bernanke and Kuttner (2005), I decompose the responses of portfolio returns to monetary policy actions across the three components of equity excess returns—cash-flow news, discount rate news, and real interest rate news. This analysis provides additional evidence to the literature on the equity return decomposition, and the relative importance of cash-flow news and discount rate news in driving stock returns (Campbell, 1991; Campbell and Ammer, 1993; Vuolteenaho, 2002; Larrain and Yogo, 2008; Chen and Zhao, 2009; Campbell, Giglio, and Polk, 2012; Garret and Priestley, 2012, among others).

The results can be summarized as follows. The monthly impact of changes in the ΔFFR is greater for the returns of more financially constrained stocks

than for the returns of stocks with a more favorable financial position. More importantly, using a VAR methodology, the results show that the negative effect of FFR shocks on stock returns comes from a corresponding negative effect on future expected cash flows (cash-flow news), which is stronger than the impact on future equity risk premia (discount rate news). Thus, cash-flow news is the main return component affected by ΔFFR. These results are reasonably robust to different VAR specifications and identifications schemes. Specifically, in addition to the traditional identification employed in the return decomposition literature (estimating cash-flow news as the residual component of stock returns), I directly estimate portfolio cash-flow news by including portfolio dividend growth in the VAR specification. Another important result is that the dispersion in return responses to monetary shocks across stocks with different degrees of financial constraints (small versus large and value versus growth) is explained by a similar dispersion in the effects on cash-flow news, which outweighs the dispersion in discount rate news betas.

This article is closely related to Bernanke and Kuttner (2005), although it differs from it in several important ways. First, I use different variables to measure monetary policy shocks. Second, I seek to evaluate the impact of monetary policy on the cross-section of stock returns, whereas Bernanke and Kuttner (2005) focus on stock market returns. This work is also closely related to Patelis (1997), Goto and Valkanov (2002), and Maio (2012a) in terms of the proxies for monetary policy, although the focus is on measuring the contemporaneous monthly effect on returns, while their goal is to quantify the forecasting ability of the FFR for stock returns. Thorbecke (1997) uses a VAR-based approach to quantify the impact of shocks in the FFR on the returns of portfolios sorted on size. However, that paper does not measure the effect of monetary actions in the components of stock returns—cash flow and discount rate news. Similarly to this article, Guo (2004) conducts simple regressions to analyze the impact of changes in FFR on size and book-to-market portfolios. Nevertheless, I use different proxies for monetary policy actions, and more importantly, take a VAR approach to relate the portfolio responses to the components of portfolio returns, in addition to using a more complete set of portfolio classes in the analysis.

This work is also related to the cross-sectional asset pricing studies showing that value stocks enjoy higher average returns than growth stocks because they have higher interest rate risk (i.e., value stocks have more negative betas against short-term interest rates than growth stocks) given the negative risk price estimated for the interest rate factor (see, e.g., Brennan, Wang, and Xia, 2004; and Lioui and Maio, 2012). The results in

the article show that the more negative interest rate betas for value (small) stocks compared to growth (large) stocks is associated with a dispersion in betas for future stock cash flows rather than stock discount rates. These results can also be linked with the theoretical model developed by Li and Palomino (2009) in which the effect of monetary policy shocks on the cross-section of stock returns is decomposed into two opposite effects—an output effect and a markup effect. Specifically, an increase in the FFR leads to a sharper output decline in firms with more rigid product prices, which points to a higher expected return on the stocks of these firms. However, these firms also face a larger increase in their markups, which points to lower expected returns. If the second effect dominates the former, the stocks of the firms with more rigid prices provide a hedge for consumption, and investors require a lower expected return to hold these stocks in comparison to the stocks associated with firms having more flexible product prices. To the extent that small and value firms face more sticky product prices than large and growth firms, the results in this article showing higher expected returns (following an increase in the FFR) for small and value stocks compared to large and growth stocks, respectively, provides evidence that the output effect might dominate the markup effect.

The remainder of this article is organized as follows. Section 2 describes the data and variables, whereas Section 3 presents the results for the impact of monetary policy shocks on the cross-section of portfolio returns. Section 4 relates these responses to the fundamental components of stock returns—cash flow and discount rate news, whereas Section 5 presents robustness checks to the VAR analysis. Section 6 concludes.

2. Data and Variables

2.1 PORTFOLIO DATA AND OTHER VARIABLES

To assess the explanatory power of monetary policy on the cross-section of excess stock returns, I use return data for decile portfolios sorted according to four characteristics. The portfolio groups are the Fama and French (1992, 1996) portfolios sorted on size (market capitalization, S10); book-to-market (book value-to-market capitalization ratio, BM10); earnings-to-price ratio (EP10); and cash flow-to-price ratio (CP10). To compute excess returns, I subtract the 1-month Treasury bill rate. The data on S10, BM10, EP10, CP10, and the 1-month Treasury bill rate are obtained from Kenneth French's Webpage. The data on the value-weighted stock market return are from the Center for Research in Security Prices (CRSP). Using equity portfolios rather than individual stocks to measure the response of returns to
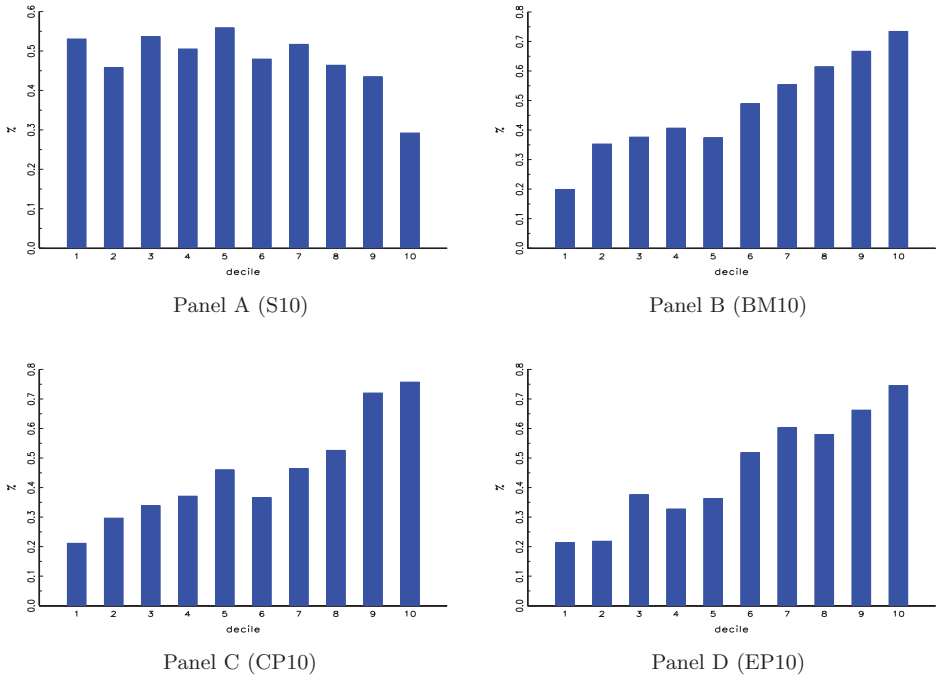
Panel A (S10)

Panel B (BM10)

Panel C (CP10)

Panel D (EP10)

Figure 1. Average portfolio returns. This figure plots the average excess (log) returns (in %) for S10, BM10, CP10, and EP10. The sample is 1963:07–2008:06.

monetary policy actions has some advantages. First, one mitigates the measurement error associated with the reactions to monetary actions, which should be estimated with substantial noise in the case of individual stocks (particularly, small and illiquid stocks). Second, by using portfolios one can relate the monetary responses to size and book-to-market, which are related with the financial distress of firms, thus providing a direct test of the theories of monetary transmission to stock returns, discussed in Section 1.[3]

Figure 1 displays the average excess log returns for the four portfolio groups. We can see that, in average, small stocks earn higher returns than big stocks, the so-called size premium. On the other hand, value stocks (higher deciles on BM10, CP10, and EP10) have higher average returns

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[3] For example, Whited and Wu (2006) find that financial constraints are negatively correlated with size, whereas Fama and French (1995) show that value firms tend to have persistent lower earnings, and hence are more financially constrained, than growth firms.

than the corresponding lower deciles (growth stocks), which corresponds to the value premium (Fama and French, 1992). In other words, more financially constrained stocks have higher returns in average than less constrained stocks.

The state variables used in the VAR analysis conducted in Section 4 are the 1-month real interest rate (r_r); the change in the 1-month nominal Treasury bill rate (Δr_f); the relative 3-month bill rate (RREL); the slope of the Treasury yield curve (TERM); and the log market dividend-to-price ratio $(d - p)$. To compute the real interest rate, I use the CPI inflation rate. RREL represents the difference between the 3-month bill rate and a backward moving average over the last 12 months, $RREL_t = r3_t - \sum_{j=1}^{12} r3_{t-j}$. TERM is measured as the yield spread between 10-year and 1-year Treasury bonds, while the aggregate dividend-to-price ratio corresponds to the log ratio of annual dividends to price associated with the Standard and Poors (S&P) 500 index. The CPI, interest rate, and bond yield data are available from the FRED database (St Louis Fed). The S&P 500 dividend and price data are obtained from Robert Shiller's Webpage.

In Section 5, I conduct alternative VAR identifications that rely on individual portfolio dividend-to-price ratios and portfolio dividend growth. Both variables can be computed for each portfolio from the time-series of total return and return excluding dividends. Specifically, the dividend-to-price ratio of portfolio i is computed as

$$\frac{D_{i,t+1}}{P_{i,t+1}} = \frac{R_{i,t+1}}{R^*_{i,t+1}} - 1, \tag{1}$$

where $D_{i,t+1}$ denotes the dividend level; $P_{i,t+1}$ is the price level for portfolio i; $R_{i,t+1}$ represents the total gross return; and $R^*_{i,t+1}$ denotes the gross return excluding dividends. Similarly, the gross dividend growth of portfolio i is given by

$$\frac{D_{i,t+1}}{D_{i,t}} = \frac{R_{i,t+1} - R^*_{i,t+1}}{R_{i,t} - R^*_{i,t}} R^*_{i,t}. \tag{2}$$

The data on the portfolio returns excluding dividends are obtained from Kenneth French's Webpage.

Figure 2 shows the average portfolio dividend-to-price ratios, $\frac{D_{i,t+1}}{P_{i,t+1}} \times 100$, for the four portfolio groups. The plots show that big and value stocks have larger dividend-to-price ratios than small and growth stocks. Moreover, this relation between dividend-to-price ratio with either size or value is close to being monotonic. This is consistent with the evidence in Fama and French (2001) that a decline in aggregate dividends trough time is associated with a
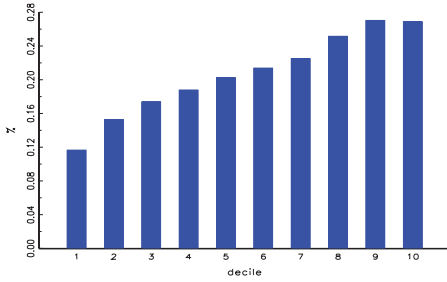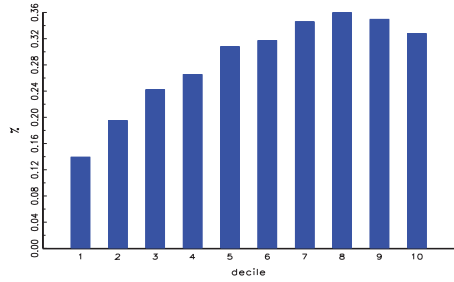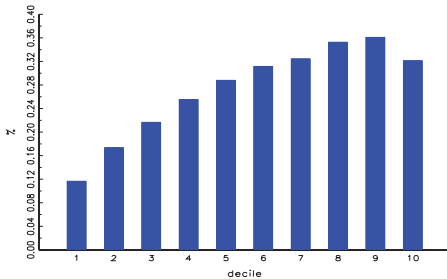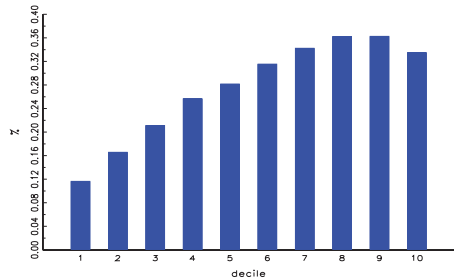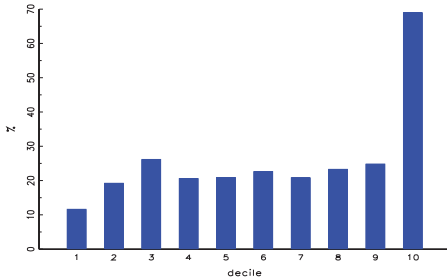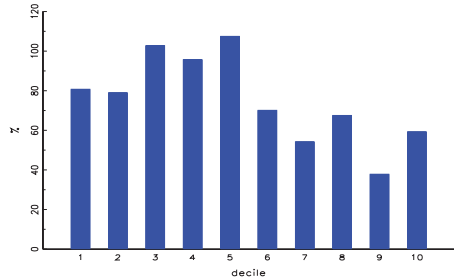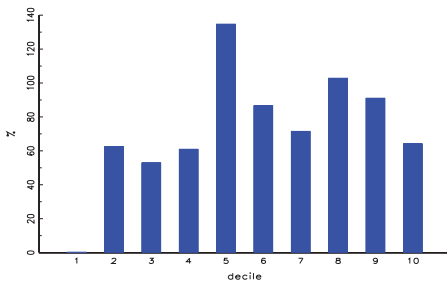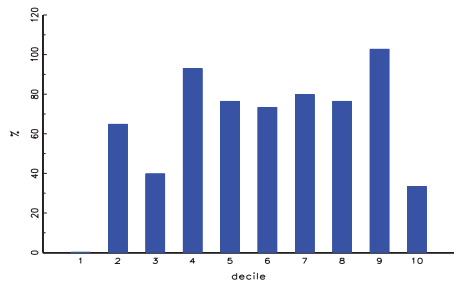
Figure 2. Average portfolio dividend-to-price ratios and dividend growth. This figure plots the average monthly dividend-to-price ratios (Panels A–D) and average monthly dividend growth (Panels E–H), both in %, for S10, BM10, CP10, and EP10. The sample is 1963:07–2008:06.

change in the stock market structure toward smaller firms with large invest-ment opportunities.

The average monthly portfolio net dividend growth rates, $\left(\frac{D_{i,t+1}}{D_{i,t}} - 1\right) \times 100$, are also displayed in Figure 2 (Panels E–H). In the case of the size portfolios, the dividend growth rate for the biggest decile is sig-nificantly greater than for the remaining deciles. Regarding the book-to-market portfolios, growth stocks have higher dividend growth rates than value stocks in average, whereas for the cash flow-to-price deciles there seems to occur an inverse relation. In the case of EP10, there is no clear trend for dividend growth across deciles.[4]

2.2 IDENTIFYING MONETARY POLICY ACTIONS

Two proxies for monetary policy actions are used in the article. The first measure is the change in the Fed funds rate, $\Delta\text{FFR}_t = \text{FFR}_t - \text{FFR}_{t-1}$. This proxy has been widely used in the literature (Patelis, 1997; Thorbecke, 1997; Goto and Valkanov, 2002; Jensen and Mercer, 2002; Chen, 2007, among others). Bernanke and Blinder (1992) and Bernanke and Mihov (1998) argue that the FFR is a good proxy for the Fed policy actions, whereas Fama (2012) shows that the FFR tends to adjust relatively fast to the Fed funds target rate. However, several other monetary policy proxies have been proposed in the literature. For example, Kuttner (2001) proposes the change in the implied rate of the Fed funds futures contract as a proxy for the unanticipated change in monetary policy. Faust, Swanson, and Wright (2004), Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2007), Basistha and Kurov (2008), and Hamilton (2009), among others, use this method. Another approach is to use high-frequency financial data to indirectly identify monetary policy shocks (Cochrane and Piazzesi, 2002; Rigobon and Sack, 2003, 2004). Ehrmann and Fratzscher (2004) estimate the surprise in Fed policy as the difference between the announcement of the FOMC decision and the average expectation among investors. In related work, Gürkaynak, Sack, and Swanson (2005) use the FOMC statements as an indicator of the "future path of policy".

For the purposes in this article, in which one estimates a VAR and computes the responses of equity returns and its VAR-based components to monetary actions, a regular time-series is needed. This is not compatible with

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[4] For the first decile within CP10 and EP10, the dividend level is zero for a few months, and thus, the log dividend growth rate and log dividend yield are not well defined in those periods. To resolve this problem, in Section 5 below, I use the dividend-to-price ratio and dividend growth of the corresponding second decile.

some of the other proxies that are used in an event study context. Moreover, by using ΔFFR, I am able to use a longer sample than some alternative measures (as the implied futures rate), which is crucial to obtain more precise estimates in the VAR dynamics and the implied return components' reactions to monetary policy shocks. The data on the FFR are from FRED.

The second proxy for monetary policy shocks is the Fed funds premium (FFPREM), that is, the difference between FFR and the lagged 1-month Treasury bill rate:

$$\text{FFPREM}_t = \text{FFR}_t - \text{R}_{f,t-1}.$$

This proxy (or similar spreads) has been used by Bernanke and Blinder (1992), Jensen, Mercer, and Johnson (1996), and Cochrane and Piazzesi (2002), among others. Given that short-term interest rates observed in the previous period should reflect all anticipated changes in FFR for the current period, one can argue that any shock in FFR in excess of lagged spot short-term interest rates captures unanticipated monetary policy shocks.[5] Thus, this proxy is similar in spirit to the spread of the FFR with the implied futures rate used by Kuttner (2001) and Bernanke and Kuttner (2005), and has the advantage of allowing one to use a longer sample.[6] Figure 3 shows that the two monetary proxies track each other, although the correlation is only moderate (0.53). The descriptive statistics presented in Table I show that FFPREM is both more volatile and persistent than ΔFFR, which is consistent with the results obtained in Balduzzi et al. (1998) and Fama (2012).

3. Estimating the Monthly Effect of Monetary Policy Actions on Stock Returns

In this section, I estimate the (contemporaneous) monthly effect of changes in the FFR on the cross-section of equity returns. As in Bernanke and Kuttner (2005), I conduct the following regressions, estimated on a monthly basis:

$$r_{i,t} = a^i + b^i \Delta \text{FFR}_t + \varepsilon_{i,t}, \tag{3}$$

$$r_{i,t} = a^i + b^i \text{FFPREM}_t + \varepsilon_{i,t}. \tag{4}$$

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[5] Balduzzi, Bertola, and Foresi (1997) and Heidari and Wu (2010) provide evidence that short-term interest rates anticipate future changes in the Fed funds rate target.

[6] In the article, I use interchangeably the terms monetary policy actions and shocks. However, some authors use "monetary policy actions" to refer to the total change in the Fed funds rate (ΔFFR), and use "monetary policy shocks" as denoting the unexpected or surprise change in monetary policy, for which FFPREM should be a convenient proxy.
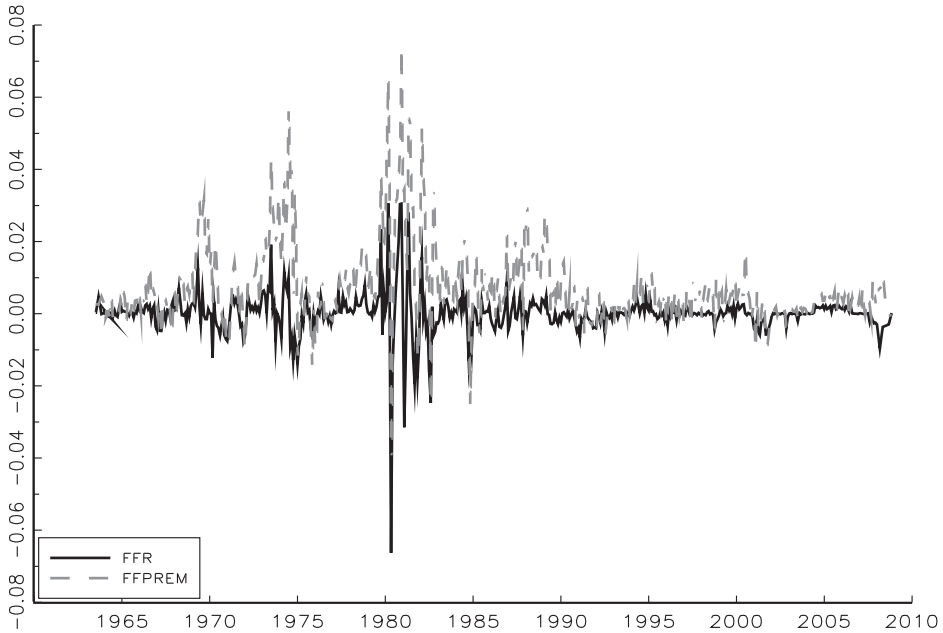
Figure 3. Monetary policy proxies. This figure plots the time-series for the monthly change in the FFR and the Fed funds premium (FFPREM). The sample period is 1963:07–2008:06.

Above, $r_{i,t} \equiv \ln(R_{i,t}) - \ln(R_{f,t})$ denotes the excess log return on equity portfolio i ($i = 1, \ldots, 10$), and $\varepsilon_{i,t}$ represents the component of the portfolio return not explained by monetary policy changes. The slope coefficient, b^i, measures the response of stock prices (returns) to monetary actions. The full sample coincides with the period from 1963:07 to 2008:06. The above regression is estimated by OLS (equation-by-equation) for each decile in the portfolio sorting groups described in Section 2 above.

  As an early motivation for the upcoming analysis for portfolios, I estimate the above regressions for the value-weighted excess equity market return (r_m). In the case of ΔFFR, the slope estimate is -1.20, which translates into -14.34 on an annual basis, and it is statistically significant at the 1% level.[7] This estimated response of r_m is in line with the slopes obtained in Bernanke and Kuttner (2005) with monthly data, discounting for the different monetary policy proxies and different samples used in

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[7] The *t*-statistics are calculated under Newey and West (1987) standard errors with five lags.

Table I. Descriptive statistics for monetary proxies

This table reports descriptive statistics for the monetary policy proxies (ΔFFR and FFPREM) and VAR state variables used in Section 4. The state variables are the 1-month real interest rate (r_r); the change in the 1-month nominal Treasury bill rate (Δr_f); the relative 3-month bill rate (RREL); the slope of the Treasury yield curve (TERM); the log market dividend-to-price ratio ($d - p$); and the excess log market return (r_m). The sample is 1963:07–2008:06. ϕ designates the first-order autocorrelation. The correlations between the variables are presented in Table II.

	Mean	Stdev.	Min.	Max.	ϕ
ΔFFR	−0.000	0.006	−0.066	0.031	0.401
FFPREM	0.007	0.011	−0.041	0.074	0.653
r_r	0.001	0.003	−0.011	0.012	0.513
Δr_f	−0.000	0.001	−0.005	0.004	−0.162
RREL	−0.000	0.011	−0.042	0.046	0.904
TERM	0.008	0.011	−0.031	0.033	0.967
$d - p$	−3.579	0.415	−4.495	−2.801	0.997
r_m	0.004	0.044	−0.261	0.148	0.064

the two studies.[8] When the monetary proxy is FFPREM the slope estimate is −0.84, which is significant at the 1% level.

3.1 PORTFOLIOS SORTED BY SIZE

When the monetary proxy is ΔFFR, the slopes, and respective *t*-statistics, associated with regression (3) for different portfolio sorts are displayed in Figure 4. In the case of FFPREM, the slopes, and associated *t*-stats, are presented in Figure 5. The portfolio groups are S10, BM10, CP10, and EP10. Table III presents the difference in slopes across extreme deciles within each portfolio group, and the associated Wald statistics. The first dispersion measure (Dif$_1$) stands for the difference between the slopes of the extreme first and last deciles, $b^1 - b^{10}$; the second dispersion proxy (Dif$_2$) denotes the difference in average slopes between the first two deciles and last two deciles, $\frac{1}{2}(b^1 + b^2) - \frac{1}{2}(b^9 + b^{10})$; whereas the third spread (Dif$_3$) represents the difference in average slopes between the first three deciles and last three deciles, $\frac{1}{3}(b^1 + b^2 + b^3) - \frac{1}{3}(b^8 + b^9 + b^{10})$. The corresponding null

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[8] Bernanke and Kuttner (2005) report a response to the surprise change in monetary policy of −11.43 annually, and a response to the expected change of −1.11, resulting in a total response of −12.54.
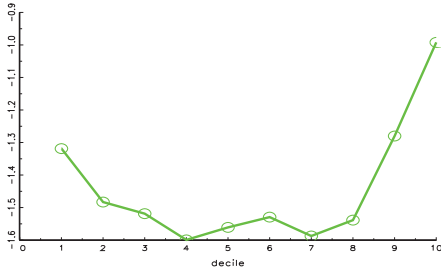
Panel A (S10)
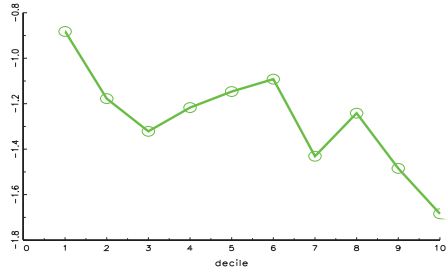
Panel B (BM10)
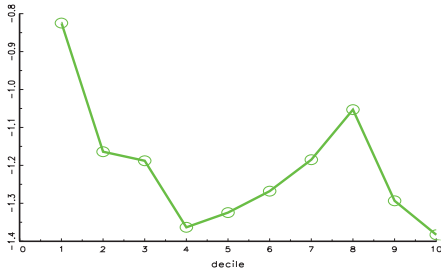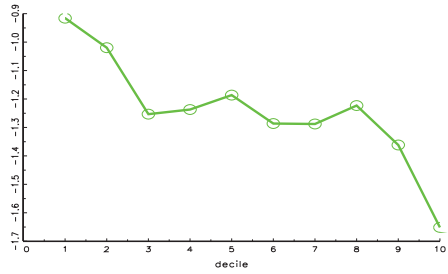
Panel C (CP10)

Panel D (EP10)
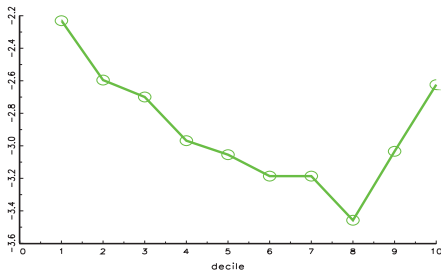
Panel E (S10, t-stats)
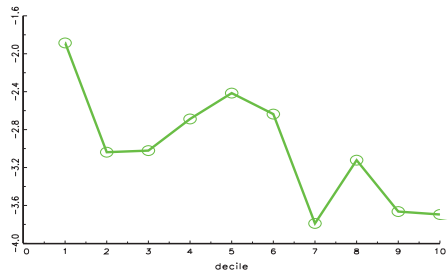
Panel F (BM10, t-stats)
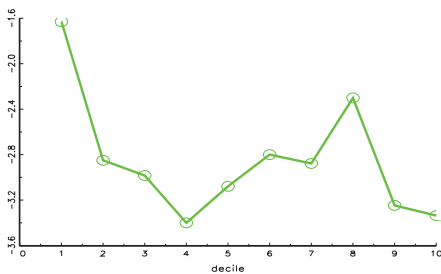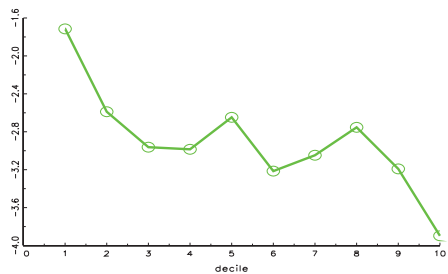
Panel G (CP10, t-stats)

Panel H (EP10, t-stats)

Figure 4. Monthly effect of ΔFFR on portfolio returns. This figure plots the monthly responses, and associated *t*-statistics, of portfolio returns to monetary policy actions. The monetary policy proxy is ΔFFR. The monthly regressions are conducted for portfolio groups S10, BM10, CP10, and EP10. The *t*-statistics are based on the Newey–West standard errors computed with five lags. The sample is 1963:07–2008:06.
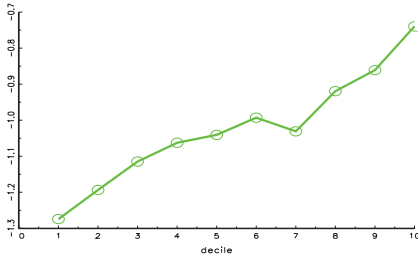
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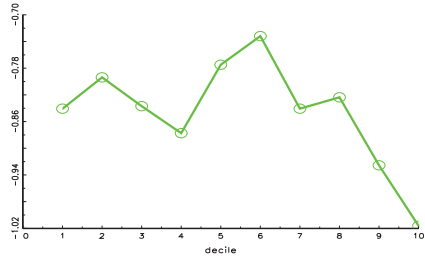
Panel B (BM10)
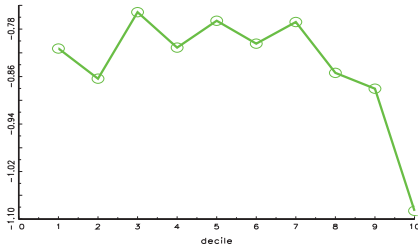
Panel C (CP10)
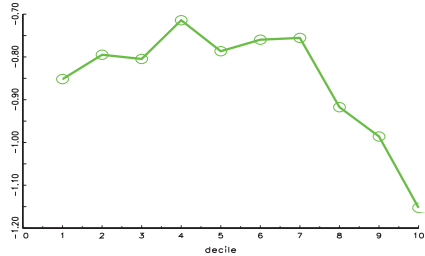
Panel D (EP10)
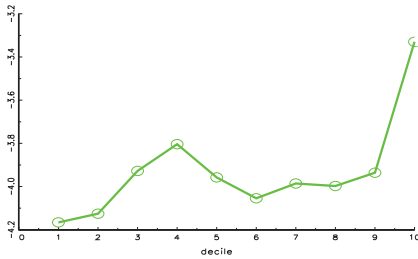
Panel E (S10, t-stats)
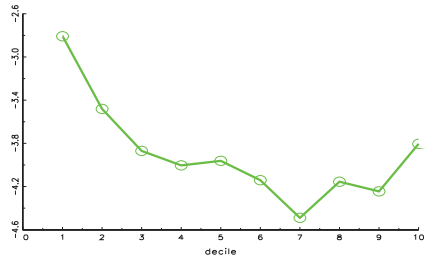
Panel F (BM10, t-stats)
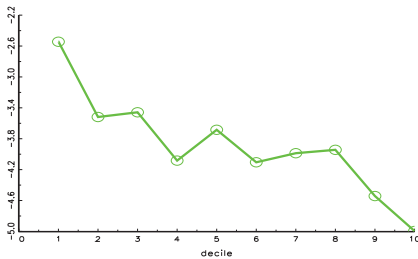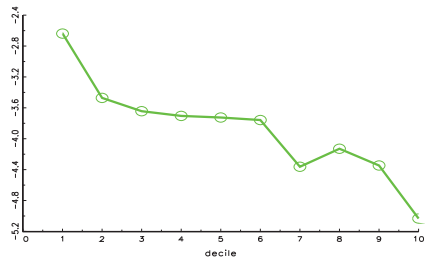
Panel G (CP10, t-stats)

Panel H (EP10, t-stats)

Figure 5. Monthly effect of FFPREM on portfolio returns. This figure plots the monthly responses, and associated *t*-statistics, of portfolio returns to monetary policy actions. The monetary policy proxy is FFPREM. The monthly regressions are conducted for portfolio groups S10, BM10, CP10, and EP10. The *t*-statistics are based on the Newey–West standard errors computed with five lags. The sample is 1963:07–2008:06.

Table II. VAR state variables

	ΔFFR	FFPREM	r_r	Δr_f	RREL	TERM	$d-p$	r_m
ΔFFR	1.00	0.53	-0.05	0.45	0.49	-0.21	-0.03	-0.16
FFPREM		1.00	-0.01	0.56	0.50	-0.51	0.33	-0.22
r_r			1.00	0.07	-0.15	-0.01	0.04	0.13
Δr_f				1.00	0.35	-0.17	-0.00	-0.15
RREL					1.00	-0.58	0.02	-0.17
TERM						1.00	-0.17	0.12
$d-p$							1.00	-0.00
r_m								1.00

hypothesis of equality across responses associated with opposite deciles can be stated in all three cases as

$$\mathbf{R}\boldsymbol{\delta} = r, \tag{5}$$

in which $r = 0$ and $\boldsymbol{\delta} \equiv (a^1, b^1, a^2, b^2, \ldots, a^{10}, b^{10})'$ denotes a stacked vector of coefficients. What differs across the three hypotheses is the coefficients matrix $\mathbf{R}$, which is given by $\mathbf{R} = [0, 1, 0, \ldots, 0, 0, -1]$ in the case of Dif$_1$, for example.[9]

Panel A in Figure 4 shows that the return response to ΔFFR is greater (in magnitude) for small stocks compared to big stocks. However, the relation between size and the responses to monetary shocks is not monotonic, being more like u-shaped, that is, intermediate capitalization stocks show the larger responses (in magnitude). The corresponding *t*-statistics for the size portfolio responses point to statistical significance at the 5% or 1% levels, that is, monetary shocks have a strong effect on the returns of size portfolios. The difference in average responses across the opposite deciles range between -0.17 (Dif$_3$) and -0.33 (Dif$_1$), but these spreads are not statistically different from zero (*p*-values above 0.33). Thus, small stocks seem to be more responsive to the FFR than big stocks, in line with previous evidence showing that small firms are more sensitive to monetary policy tightening than large firms (e.g., Gertler and Gilchrist, 1994; Perez-Quiros and Timmermann, 2000). However, there is a large statistical uncertainty

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[9] The Wald test statistic is

$$W = T\left(\mathbf{R}\widehat{\boldsymbol{\delta}} - r\right)'\left\{\mathbf{R}\left[T\mathrm{Var}\left(\widehat{\boldsymbol{\delta}}\right)\right]\mathbf{R}'\right\}^{-1}\left(\mathbf{R}\widehat{\boldsymbol{\delta}} - r\right) \to_d \chi^2(1),$$

where $\mathrm{Var}\left(\widehat{\boldsymbol{\delta}}\right)$ denotes the variance–covariance matrix associated with the coefficient estimates (Hayashi, 2000).

embedded in this relation, which might be related to previous evidence showing that the size effect is not existent in the 1990s (Guo, 2004).

When the monetary proxy is FFPREM, the relation between size and the response to monetary shocks is much closer to a monotonic one, and the portfolio responses are strongly significant, as shown in Panels A and E of Figure 5. Moreover, the spreads in average responses across the opposite deciles are stronger than in the case of ΔFFR, varying between -0.35 (Dif_3) and -0.54 (Dif_1), and these differences are strongly significant as indicated by the corresponding p-values around 1%. Therefore, these results show that changes in FFPREM have a more pronounced asymmetric effect on small stocks (in comparison to big stocks) than the total change in the FFR.

3.2 PORTFOLIOS SORTED ON THE BOOK-TO-MARKET RATIO

For the case of portfolios sorted on the book-to-market ratio (BM) and using ΔFFR as policy proxy, there is a positive relationship between the magnitudes of the responses and book-to-market. With the exception of the first decile, the slope estimates are statistically significant at the 5% or 1% levels. Thus, the response is much stronger for the extreme value portfolio (tenth decile) than for the extreme growth portfolio (first decile), yielding a spread of 0.80. In the case of Dif_2 one obtains a spread of 0.55. In both cases, the p-values associated with the Wald statistic are below 5%, thus rejecting the null hypothesis that the average responses among the growth and value portfolios are equal. The estimate for Dif_3 is also positive but of lower magnitude (0.34), and we reject the null at the 10% level (p-value of 7%). In sum, value stocks react more to changes in the FFR than growth stocks for the sample in analysis.

In the case of FFPREM, we also have a positive relation between book-to-market and the magnitudes of portfolio responses. However, the spreads in average responses for opposite deciles are significantly smaller than in the regression with ΔFFR, varying between 0.10 (Dif_3) and 0.18 (Dif_1), and these gaps are not statistically significant at the 10% level.

3.3 PORTFOLIOS SORTED ON CASH FLOW-TO-PRICE AND EARNINGS-TO-PRICE

I examine two additional classes of portfolios sorted on fundamentals-to-price ratios—ten portfolios sorted on cash flow-to-price and earnings-to-price ratios. Similarly to the book-to-market portfolios, these two portfolio groups represent a measure of value, and thus, the lower deciles are associated with growth stocks, whereas the higher deciles represent value

stocks. As in the case of BM10, for both portfolio groups the value port-
folios have a larger response (in magnitude) to ΔFFR than growth stocks,
and this pattern is stronger in the case of the EP10 portfolios. For both
groups, the slope estimates are statistically significant at the 5% or 1%
levels, with the sole exception of the extreme growth portfolio (first
decile). In the case of CP10 the spreads in responses vary between 0.18
(Dif_3) and 0.56 (Dif_1), and both Dif_1 and Dif_2 are significant at the 10%
level. Regarding the EP10 portfolios the spreads in the slopes vary between
0.35 (Dif_3) and 0.74 (Dif_1), and the null hypothesis (that the extreme deciles'
slopes are identical) is rejected at the 5% level in all three tests. Hence,
monetary policy actions have a stronger impact on the monthly returns of
value stocks compared to growth stocks.[10] The intuition is as follows. Many
of these value stocks are associated with firms that were exposed to persist-
ent negative shocks in their profitability (Fama and French, 1995), and thus
have depressed stock prices. In turn, this implies that the cost of external
funding is greater for these firms, implying that they will be more sensitive to
additional negative shocks in their profitability and/or increases in their cost
of external finance (increases in interest rates).

   When one uses FFPREM as monetary policy instrument, it turns out
that value stocks continue to be more responsive than growth stocks,
with the individual portfolio responses being statistically significant for all
deciles among the two portfolio groups. However, as in the case of the
book-to-market portfolios, the positive gaps in average slopes between
growth and value stocks are not statistically significant at the 10% level.
Thus, the asymmetric effect of monetary policy on value versus growth
stocks is more pronounced for the ΔFFR in comparison to FFPREM.

3.4 CONTROLLING FOR THE BUSINESS CYCLE

Since both equity premia and monetary policy actions are influenced by
business conditions, it is important to control for business cycle indicators
when assessing the impact of monetary policy on stock returns. I use three
proxies for the business cycle: the slope of the yield curve (TERM), the
default spread (DEF), and the log market dividend-to-price ratio ($d - p$).
Fama and French (1989), among others, use these three variables as business
cycle proxies that forecast the aggregate equity premium. To evaluate the

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[10] In a recent working paper (produced after the first versions of this article), Kontonikas
and Kostakis (2011) reach similar results.

effect of monetary policy actions, I estimate the following augmented regressions:

$$r_{i,t} = a^i + b^i\Delta\text{FFR}_t + c^i\text{TERM}_t + d^i\text{DEF}_t + e^i(d_t - p_t) + \varepsilon_{i,t}, \qquad (6)$$

$$r_{i,t} = a^i + b^i\text{FFPREM}_t + c^i\text{TERM}_t + d^i\text{DEF}_t + e^i(d_t - p_t) + \varepsilon_{i,t}. \qquad (7)$$

The difference in average slopes across extreme deciles within each portfolio group, and the associated Wald statistics are reported in Table IV. The results are not qualitatively very different from those reported in Table III. For both monetary proxies the magnitudes of the spreads in responses across extreme deciles are either marginally lower or similar to the corresponding spreads in the benchmark regressions without business cycle variables. Moreover, the p-values associated with these spreads point to the same qualitative statistical decisions than in the benchmark tests. Thus, after controlling for business conditions, it still holds that value stocks are more responsive than growth stocks to the total change in the FFR, whereas small stocks react more than big stocks to variations in FFPREM.

To control for the possibility that both individual portfolio returns and the monetary policy variables react to changes in the stock market return (Rigobon and Sack, 2003, 2004), I estimate alternative multiple regressions that include the aggregate equity premium, $r_{m,t}$, as a control variable:[11]

$$r_{i,t} = a^i + b^i\Delta\text{FFR}_t + c^i\text{TERM}_t + d^i\text{DEF}_t + e^i(d_t - p_t) + f^i r_{m,t} + \varepsilon_{i,t}, \quad (8)$$

$$r_{i,t} = a^i + b^i\text{FFPREM}_t + c^i\text{TERM}_t + d^i\text{DEF}_t + e^i(d_t - p_t) + f^i r_{m,t} + \varepsilon_{i,t}. \qquad (9)$$

Results presented in the internet appendix show that, for both monetary proxies, the spreads in responses associated with BM10, CP10, and EP10 increase in magnitude relative to Table IV, and become statistically significant in most cases. The exceptions are Dif_1 and Dif_2, which are not significant at the 10% level in the case of BM10 and using FFPREM as monetary proxy. Thus, by controlling for the market return the spread in return responses among growth/value portfolios becomes more similar across the two monetary proxies. On the other hand, the negative spreads associated with the size deciles decrease in magnitude in comparison to the regressions (6)–(7) and become non-significant when the monetary proxy is FFPREM. Therefore, controlling for the market return increases the differential effect of monetary actions on value versus growth stocks, whereas an opposite pattern holds for small versus large stocks.

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[11] I thank the referee for suggesting this analysis.

Table III. Monthly effect of monetary policy on portfolio returns

This table reports Wald tests associated with the monthly responses of portfolio returns to monetary policy actions, as described in Section 3. The monetary policy proxies are ΔFFR and FFPREM. The monthly regressions are conducted for ten portfolios sorted on size (Panels A, E); ten portfolios sorted on book-to-market (Panels B, F); ten portfolios sorted on cash flow-to-price (Panels C, G); and ten portfolios sorted on earnings-to-price (Panels D, H). Dif_1 denotes the difference in responses across extreme deciles, $b^1 - b^{10}$. Dif_2 denotes the difference in average responses between the four extreme deciles, $\frac{1}{2}(b^1 + b^2) - \frac{1}{2}(b^9 + b^{10})$, whereas Dif_3 denotes the difference in average responses between the six extreme deciles, $\frac{1}{3}(b^1 + b^2 + b^3) - \frac{1}{3}(b^8 + b^9 + b^{10})$. The columns labeled χ_1^2, χ_2^2, and χ_3^2 denote the Wald statistics associated with the null hypotheses $b^1 = b^{10}$, $\frac{1}{2}(b^1 + b^2) = \frac{1}{2}(b^9 + b^{10})$, and $\frac{1}{3}(b^1 + b^2 + b^3) = \frac{1}{3}(b^8 + b^9 + b^{10})$, respectively. The associated p-values are reported in parenthesis. The Wald statistics are based on the Newey–West standard errors computed with five lags. The sample is 1963:07–2008:06.

Dif_1	χ_1^2	Dif_2	χ_2^2	Dif_3	χ_3^2
Panel A (S10, ΔFFR)					
−0.33	0.90	−0.26	0.85	−0.17	0.48
	(0.34)		(0.36)		(0.49)
Panel B (BM10, ΔFFR)					
0.80	8.66	0.55	7.12	0.34	3.38
	(0.00)		(0.01)		(0.07)
Panel C (CP10, ΔFFR)					
0.56	3.62	0.34	2.87	0.18	1.29
	(0.06)		(0.09)		(0.26)
Panel D (EP10, ΔFFR)					
0.74	6.47	0.54	5.75	0.35	3.95
	(0.01)		(0.02)		(0.05)
Panel E (S10, FFPREM)					
−0.53	7.01	−0.43	7.05	−0.35	6.76
	(0.01)		(0.01)		(0.01)
Panel F (BM10, FFPREM)					
0.18	0.49	0.15	0.73	0.10	0.43
	(0.48)		(0.39)		(0.51)
Panel G (CP10, FFPREM)					
0.27	1.60	0.15	0.69	0.13	0.94
	(0.21)		(0.41)		(0.33)
Panel H (EP10, FFPREM)					
0.30	2.00	0.25	2.19	0.20	2.56
	(0.16)		(0.14)		(0.11)

Table IV. Monthly effect of monetary policy: controlling for the business cycle

This table reports Wald tests associated with the monthly responses of portfolio returns to monetary policy actions, as described in Section 3, by using business cycle variables as controls. The monetary policy proxies are ΔFFR and FFPREM. The monthly regressions are conducted for ten portfolios sorted on size (Panels A, E); ten portfolios sorted on book-to-market (Panels B, F); ten portfolios sorted on cash flow-to-price (Panels C, G); and ten portfolios sorted on earnings-to-price (Panels D, H). Dif$_1$ denotes the difference in responses across extreme deciles, $b^1 - b^{10}$. Dif$_2$ denotes the difference in average responses between the four extreme deciles, $\frac{1}{2}(b^1 + b^2) - \frac{1}{2}(b^9 + b^{10})$, whereas Dif$_3$ denotes the difference in average responses between the six extreme deciles, $\frac{1}{3}(b^1 + b^2 + b^3) - \frac{1}{3}(b^8 + b^9 + b^{10})$. The columns labeled χ_1^2, χ_2^2, and χ_3^2 denote the Wald statistics associated with the null hypotheses $b^1 = b^{10}$, $\frac{1}{2}(b^1 + b^2) = \frac{1}{2}(b^9 + b^{10})$, and $\frac{1}{3}(b^1 + b^2 + b^3) = \frac{1}{3}(b^8 + b^9 + b^{10})$, respectively. The associated *p*-values are reported in parenthesis. The Wald statistics are based on the Newey–West standard errors computed with five lags. The sample is 1963:07–2008:06.

Dif$_1$	χ_1^2	Dif$_2$	χ_2^2	Dif$_3$	χ_3^2
Panel A (S10, ΔFFR)					
−0.13	0.14	−0.11	0.14	−0.05	0.04
	(0.71)		(0.71)		(0.85)
Panel B (BM10, ΔFFR)					
0.73	6.10	0.54	5.83	0.36	3.16
	(0.01)		(0.02)		(0.08)
Panel C (CP10, ΔFFR)					
0.52	3.15	0.35	2.72	0.21	1.58
	(0.08)		(0.10)		(0.21)
Panel D (EP10, ΔFFR)					
0.69	5.21	0.50	4.55	0.33	3.11
	(0.02)		(0.03)		(0.08)
Panel E (S10, FFPREM)					
−0.50	3.50	−0.45	4.24	−0.38	4.34
	(0.06)		(0.04)		(0.04)
Panel F (BM10, FFPREM)					
0.17	0.34	0.18	0.78	0.14	0.65
	(0.56)		(0.38)		(0.42)
Panel G (CP10, FFPREM)					
0.25	0.88	0.17	0.64	0.16	1.01
	(0.35)		(0.42)		(0.31)
Panel H (EP10, FFPREM)					
0.34	1.69	0.26	1.70	0.20	1.68
	(0.19)		(0.19)		(0.20)

3.5 SUBSAMPLE ANALYSIS

I conduct a subsample analysis by estimating regressions (3)–(4) for the 1963:07–1982:12 and 1983:01–2008:06 periods. The objective is to gauge the stability of the findings reported above over time.[12] The first period correspond to the pre-Volcker period and the second period is known as the Volcker–Greenspan era.[13] Results tabulated in the internet appendix show that the magnitudes of the spreads in slopes associated with the size portfolios are greater in the modern period than in the pre-Volcker period, although in both cases these gaps are not statistically significant at the 10% level. Regarding the value/growth portfolios, the dispersion in responses has lower magnitudes in the second period in comparison to the first period in the case of BM10 and CP10, whereas an opposite pattern holds for EP10. However, these spreads are not statistically significant in the modern sample.

When the monetary proxy is FFPREM, in the case of the size portfolios the dispersion in slopes between small and big stocks increases (in magnitude) in the second period, and these gaps are statistically significant in both periods. On the other hand, for BM10, CP10, and EP10, the magnitudes of the spreads between growth and value portfolios also increase in the second period, but there is no statistical significance, with the exception of EP10 (Dif_1). Overall, these results provide evidence that the greater effect of FFPREM on small (versus big stocks) remains robust across the two periods, whereas the sharper effect of ΔFFR on value versus growth stocks is more pronounced on the pre-Volcker period. This trend may be consistent with previous evidence suggesting that monetary policy actions have less impact in the economy in recent years (Boivin and Giannoni, 2006).

Following Bernanke and Kuttner (2005) and Fama (2012), I also conduct a subsample analysis for the periods before and after February 1994, when the Fed started announcing explicitly changes in the Federal funds rate target. Results tabulated in the internet appendix show that in most cases the magnitudes of the spreads in slopes increase in the modern period and for both monetary policy proxies. However, in most cases these spreads in monetary responses are not statistically significant at the 10% level, which should be related with the short-time span associated with the second subsample.

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[12] Jensen and Johnson (1995), Thorbecke (1997), Guo (2004), Bernanke and Kuttner (2005), and Fama (2012) also conduct a subsample analysis in evaluating the impact of monetary policy actions in stock returns and interest rates. There is also evidence that the stock and bond betas against nominal variables (e.g., inflation) change over time (see, e.g., Duarte, 2010; Ang, Brière, and Signori, 2012; and Campbell, Sunderam, and Viceira, 2012).
[13] This sample split is consistent with the analysis in Clarida, Gali, and Gertler (2000).

4. Explaining the Reaction of Stock Returns to Monetary Policy: A VAR Approach

4.1 THE VAR METHODOLOGY

The analysis pursued in the previous section seeks to quantify the contemporaneous monthly relation between shocks in monetary policy and the cross-section of equity portfolio (excess) returns. This section goes one step further and relates the effect of changes in the FFR to the fundamental components of excess stock returns—discount rate news, cash-flow news, and real interest rate news. Similar analyses have been conducted for the stock market return (e.g., Patelis, 1997; Bernanke and Kuttner, 2005) and these papers have shown that the main impact of monetary policy shocks on (the innovations of) current stock market returns works through the change in expectations about future excess market returns (discount rate news). The effect on expected future aggregate cash flows (cash-flow news), and especially on future real interest rates, are of smaller magnitudes. I extend the analysis to the cross-section of portfolio returns to gauge whether the different responses to the FFR (that are observed for extreme deciles associated with portfolios sorted according to different characteristics) are due to different effects on portfolio discount rate news, on portfolio cash-flow news, or on real interest rate news. In sum, I want to answer two major questions. Across the different portfolios, in which component of portfolio (excess) returns does the monetary policy shock has a bigger effect? Second, I want to decompose the cross-sectional dispersion in excess return responses across extreme deciles, that is, evaluate which components of the excess portfolio return explain the dispersion observed for the total return responses.

Following the work of Campbell and Shiller (1988a), Campbell (1991), and Campbell and Ammer (1993), innovations in current equity excess returns are decomposed into revisions of future expected (excess) log returns (discount rate news); revisions of future expected log real interest rates; and the residual, which is interpreted as cash-flow news (expectations of future growth in log dividends or cash flows),

$$r_{i,t+1} - E_t(r_{i,t+1}) = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j\Delta d_{i,t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{i,t+1+j}$$

$$- (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j r_{r,t+1+j} \equiv N_{i,\mathrm{CF},t+1} - N_{i,\mathrm{DR},t+1} - N_{R,t+1}, i = 1,\ldots,10,$$

$$(10)$$

where

$$N_{i,\text{CF},t+1} \equiv (\text{E}_{t+1} - \text{E}_t)\sum_{j=0}^{\infty}\rho^j\Delta d_{i,t+1+j} = r_{i,t+1} - \text{E}_t(r_{i,t+1}) + N_{i,\text{DR},t+1} + N_{R,t+1},$$

$$N_{i,\text{DR},t+1} \equiv (\text{E}_{t+1} - \text{E}_t)\sum_{j=1}^{\infty}\rho^j r_{i,t+1+j},$$

$$N_{R,t+1} \equiv (\text{E}_{t+1} - \text{E}_t)\sum_{j=0}^{\infty}\rho^j r_{r,t+1+j}, i = 1,\ldots,10,$$

represents revisions about future cash flows of portfolio i; revisions in future expected (excess) returns of portfolio i; and revisions in future real interest rates, respectively. Equation (10) represents a dynamic accounting identity that arises from the definition of stock returns. Hence, it can be considered as a definition and does not contain any behavioral or fundamental asset pricing assumptions. The parameter ρ is a discount coefficient linked to the average dividend yield of portfolio i. To be consistent with previous work (e.g., Campbell and Ammer, 1993; Campbell and Vuolteenaho, 2004; Bernanke and Kuttner, 2005; and Maio, 2012b), I assume a constant ρ across portfolios, and set its value to $0.95^{\frac{1}{12}}$, that is, an annualized dividend yield of $\sim 5\%$.

Given the dynamic identity (10), one can produce the usual variance decomposition for each portfolio's unexpected return:

$$\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})] = \text{Var}(N_{i,\text{CF},t+1}) + \text{Var}(N_{i,\text{DR},t+1}) + \text{Var}(N_{R,t+1})$$
$$- 2\text{Cov}(N_{i,\text{CF},t+1}, N_{i,\text{DR},t+1}) - 2\text{Cov}(N_{i,\text{CF},t+1}, N_{R,t+1}) + 2\text{Cov}(N_{i,\text{DR},t+1}, N_{R,t+1}).$$

$$(11)$$

This decomposition can be used to obtain the weights of the variances of portfolio cash-flow news, portfolio discount rate news, and real interest rate news (and the covariance terms between the three components) as fractions of the total portfolio return variance.[14]

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[14] In percentage terms, the variance decomposition is given by

$$1 = \frac{\text{Var}(N_{i,\text{CF},t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]} + \frac{\text{Var}(N_{i,\text{DR},t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]} + \frac{\text{Var}(N_{R,t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]}$$
$$- \frac{2\text{Cov}(N_{i,\text{CF},t+1}, N_{i,\text{DR},t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]} - \frac{2\text{Cov}(N_{i,\text{CF},t+1}, N_{R,t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]} + \frac{2\text{Cov}(N_{i,\text{DR},t+1}, N_{R,t+1})}{\text{Var}[r_{i,t+1} - \text{E}_t(r_{i,t+1})]}.$$

Given the inclusion of the covariance terms, it follows that the weight of each term can be >1 in absolute value.

Following Campbell (1991), Campbell and Ammer (1993), and Bernanke and Kuttner (2005), I employ a first-order VAR in order to estimate the unobserved components of portfolio excess returns, $N_{i,\text{DR},t+1}$, $N_{i,\text{CF},t+1}$, and $N_{i,R,t+1}$. The VAR equation below is assumed to govern the behavior of a state vector $\mathbf{x}_{it}$, which includes the portfolio excess return and other variables known in time t that help to forecast changes in equity premia,

$$\mathbf{x}_{i,t+1} = \mathbf{A}_i \mathbf{x}_{i,t} + \boldsymbol{\epsilon}_{i,t+1}, i = 1, \ldots, 10, \tag{12}$$

where the i subscript stands for portfolio i ($i = 1, \ldots, 10$).[15]

The individual news components are estimated in the following way:

$$N_{i,\text{DR},t+1} \equiv (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{i,t+1+j} = \mathbf{e1}' \rho \mathbf{A}_i (\mathbf{I} - \rho \mathbf{A}_i)^{-1} \boldsymbol{\epsilon}_{i,t+1} = \boldsymbol{\varphi}_i' \boldsymbol{\epsilon}_{i,t+1},$$

$$\tag{13}$$

$$N_{R,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{r,t+1+j} = \mathbf{e2}' (\mathbf{I} - \rho \mathbf{A}_i)^{-1} \boldsymbol{\epsilon}_{i,t+1} = \boldsymbol{\psi}_i' \boldsymbol{\epsilon}_{i,t+1}, \tag{14}$$

$$N_{i,\text{CF},t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{i,t+1+j} = r_{i,t+1} - E_t(r_{i,t+1}) + N_{i,\text{DR},t+1} + N_{R,t+1}$$

$$= \left[\mathbf{e1}' + \mathbf{e1}' \rho \mathbf{A}_i (\mathbf{I} - \rho \mathbf{A}_i)^{-1} + \mathbf{e2}' (\mathbf{I} - \rho \mathbf{A}_i)^{-1} \right] \boldsymbol{\epsilon}_{i,t+1} = \left(\mathbf{e1} + \boldsymbol{\varphi}_i + \boldsymbol{\psi}_i \right)' \boldsymbol{\epsilon}_{i,t+1},$$

$$i = 1, \ldots, 10. \tag{15}$$

In the equations above, $\mathbf{e1}$ is an indicator vector that takes a value of one in the cell corresponding to the position of the excess portfolio return in the respective VAR; $\mathbf{e2}$ plays the same role for the real interest rate; $\mathbf{A}_i$ is the VAR coefficient matrix for portfolio i; $\boldsymbol{\varphi}_i' \equiv \mathbf{e1}' \rho \mathbf{A}_i (\mathbf{I} - \rho \mathbf{A}_i)^{-1}$ is the function that relates the VAR shocks with discount rate news; and $\boldsymbol{\psi}_i' \equiv \mathbf{e2}' (\mathbf{I} - \rho \mathbf{A}_i)^{-1}$ is the function that translates the VAR shocks into real interest rate news. In Equation (15), cash-flow news is the residual component of unexpected portfolio returns, which has the advantage that one does not have to model directly the dynamics of dividends, which typically exhibit seasonality and are non-stationary. This is the typical approach used in the literature to identify the components of stock returns. In the next section, I use an alternative identification.

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[15] The VAR variables $\mathbf{x}_{it}$ are demeaned, thus one does not need to include a vector of intercepts in the VAR specification.

The state vector associated with the benchmark VAR for portfolio i is given by

$$\mathbf{x}_{i,t} \equiv \left[r_{\mathrm{r},t}, \Delta r_{\mathrm{f},t}, \mathrm{RREL}_t, \mathrm{TERM}_t, d_t - p_t, r_{i,t} \right]', i = 1, \ldots, 10, \qquad (16)$$

where r_{r} is the 1-month real interest rate; Δr_{f} denotes the change in the 1-month nominal Treasury bill rate; RREL stands for the relative 3-month bill rate; TERM represents the slope of the Treasury yield curve; and $d - p$ is the log market dividend-to-price ratio. This specification is identical to those used in Campbell and Ammer (1993) and Bernanke and Kuttner (2005). The inclusion of the real interest rate and portfolio excess returns (r_i) follows from the necessity of estimating real interest rate news and discount rate news. The inclusion of both Δr_{f} and RREL stems from the forecasting ability of these variables over the real interest rate. Moreover, there is previous evidence showing that short-term interest rates forecast excess market returns, at least for short-term forecasting horizons (see Fama and Schwert, 1977; Campbell, 1991; Hodrick, 1992; Ang and Bekaert, 2007; Maio, 2012a, among others). TERM has been widely used in the predictability of returns literature, at least since Campbell (1987) and Fama and French (1989) found that it tracks the business cycle and predicts market returns relatively well.[16] The aggregate dividend-to-price ratio is one of the most popular predictors of aggregate stock returns (Fama and French, 1988; Cochrane, 2008). Moreover, this predictor has a theoretical appeal for forecasting stock returns according to the Campbell and Shiller (1988a) decomposition.[17] The descriptive statistics from Table II show that both Δr_{f} and RREL are moderately positively correlated with both monetary policy proxies whereas TERM is negatively correlated with FFPREM.

Similarly to the time-series regressions conducted in the last section, the VAR in Equation (12) is estimated for each decile and class of portfolios analyzed in the previous sections.[18]

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[16] To be consistent with Bernanke and Kuttner (2005), I do not use the default spread (Keim and Stambaugh, 1986; Fama and French, 1989).

[17] Alternative market valuation ratios include the earnings-to-price ratio (Campbell and Shiller, 1988b; Campbell and Vuolteenaho, 2004; Maio, 2012c) or the book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998).

[18] Vuolteenaho (2002), Hecht and Vuolteenaho (2006), and Campbell, Polk, and Vuolteenaho (2010) estimate a different VAR for the whole cross-section of equities, assuming that the VAR matrix $\mathbf{A}$ is constant across stocks:

$$\mathbf{x}_{i,t+1} = \mathbf{A}\mathbf{x}_{i,t} + \boldsymbol{\epsilon}_{i,t+1}, i = 1, \ldots, N.$$

They make this assumption primarily for convenience, given the large dimension of the cross-section and survivorship bias in individual stocks. One does not have to confront the

Table V. Return forecasting regression in the benchmark VAR

This table presents the estimated coefficients and associated Newey–West t-statistics with five lags (in parenthesis) for the return equation in the benchmark VAR presented in Section 4. The VAR vector is given by $[r_{r,t}, \Delta r_{f,t}, \text{RREL}_t, \text{TERM}_t, d_t - p_t, r_{i,t}]'$ where r_r is the 1-month real interest rate; Δr_f denotes the change in the 1-month nominal Treasury bill rate; RREL stands for the relative 3-month bill rate; TERM represents the slope of the Treasury yield curve; $d - p$ is the log market dividend-to-price ratio; and r_i denotes the excess log return on portfolio i. To save space, only the results for the first (r_1) and last (r_{10}) deciles within each portfolio class are presented. The portfolio groups are S10, BM10, CP10, and EP10. The sample is 1963:07–2008:06. *, **, *** denote statistical significance of t-statistics at the 10, 5, and 1% levels, respectively. $\bar{R}^2$ is the adjusted R^2.

	$r_{r,t}$	$\Delta r_{f,t}$	RREL_t	TERM_t	$d_t - p_t$	$r_{i,t}$	$\bar{R}^2$
Panel A (S10)							
$r_{1,t+1}$	0.50	10.23	−0.69	0.22	0.01	0.24	0.08
	(0.59)	(2.58)***	(−2.24)**	(0.77)	(1.23)	(6.60)***	
$r_{10,t+1}$	1.21	3.29	−0.31	0.17	0.01	−0.02	0.01
	(1.91)*	(0.88)	(−1.34)	(0.76)	(1.11)	(−0.36)	
Panel B (BM10)							
$r_{1,t+1}$	0.92	4.85	−0.60	0.01	0.00	0.07	0.02
	(1.16)	(1.03)	(−1.95)*	(0.03)	(0.69)	(1.48)	
$r_{10,t+1}$	1.41	4.80	−0.22	0.32	0.01	0.11	0.02
	(1.88)*	(1.14)	(−0.80)	(1.22)	(1.64)	(2.76)***	
Panel C (CP10)							
$r_{1,t+1}$	0.77	5.69	−0.66	0.01	0.00	0.05	0.01
	(0.92)	(1.22)	(−2.07)**	(0.02)	(0.64)	(1.13)	
$r_{10,t+1}$	0.83	4.78	−0.34	0.36	0.00	0.02	0.01
	(1.07)	(1.33)	(−1.36)	(1.56)	(0.93)	(0.54)	
Panel D (EP10)							
$r_{1,t+1}$	0.85	5.45	−0.71	0.02	0.00	0.05	0.02
	(0.98)	(1.17)	(−2.00)**	(0.07)	(0.48)	(1.09)	
$r_{10,t+1}$	0.92	5.43	−0.39	0.32	0.00	0.09	0.02
	(1.17)	(1.47)	(−1.55)	(1.29)	(0.95)	(2.05)**	

When the above VAR is estimated for the excess market return, I obtain an adjusted R^2 of 1.58% in the equation for the market return. This goodness-of-fit is in line with previous results and shows how difficult it is

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same issues here since the analysis is based on portfolios. Moreover, estimating a specific VAR for each portfolio is likely to produce more accurate estimates of both portfolio discount rate news and cash-flow news.

Panel A (S10)   Panel B (BM10)

Panel C (CP10)   Panel D (EP10)
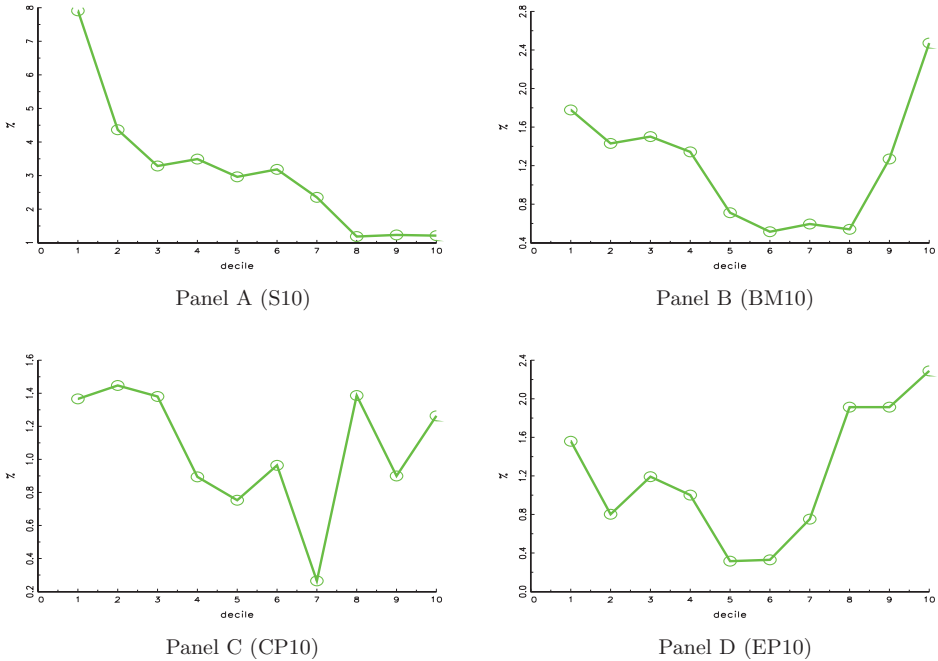
Figure 6. R^2 for portfolio VAR return equation. This figure plots the adjusted coefficient of determination associated with the (excess) portfolio return equation in the benchmark VAR presented in Section 4. The analysis is conducted for ten portfolios sorted on size (Panel A); book-to-market (Panel B); cash flow-to-price (Panel C); and earnings-to-price (Panel D). The sample is 1963:07–2008:06.

to forecast aggregate returns at the monthly horizon. The results presented in Table V and Figure 6 show that there is a significant dispersion in the predictability of excess returns across different deciles within each portfolio group. In the case of the size portfolios, apart from the last three deciles (large stocks), the R^2 estimates are above 2% (above 4% for the first two deciles (small stocks)). The greater predictability of the returns of small stocks is partially attributable to the forecasting power of both Δr_{f} and RREL. In the case of the book-to-market portfolios the fit in the return equation of the first (growth) and last (value) deciles outperforms the fit for the aggregate equity premium. However, the excess returns on the remaining BM deciles are more difficult to forecast than the excess market return. This pattern also holds approximately for the CP10 and EP10 portfolios, that is, the excess returns of the intermediate deciles are more difficult to predict than the excess returns of the extreme growth and value portfolios.

The results for the variance decomposition in Equation (11) associated with the excess market return are as follows:

$$\frac{\text{Var}\big(N_{\text{m,CF},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]} + \frac{\text{Var}\big(N_{\text{m,DR},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]} + \frac{\text{Var}\big(N_{\text{R},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]}$$

$$- \frac{2\text{Cov}\big(N_{\text{m,CF},t+1}, N_{\text{m,DR},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]} - \frac{2\text{Cov}\big(N_{\text{m,CF},t+1}, N_{\text{R},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]} + \frac{2\text{Cov}\big(N_{\text{m,DR},t+1}, N_{\text{R},t+1}\big)}{\text{Var}\big[r_{\text{m},t+1} - \text{E}_t(r_{\text{m},t+1})\big]}$$

$$= 31.25\ \% + 41.70\ \% + 1.19\ \% + 23.44\ \% - 0.20\ \% + 2.63\ \% = 100\ \%.$$

These results are consistent with previous findings showing that the major component of aggregate (unexpected) stock returns is discount rate news followed by cash-flow news, whereas real interest rate news plays a residual role (Campbell and Ammer, 1993; Campbell and Vuolteenaho, 2004; and Bernanke and Kuttner, 2005, among others).

The variance decompositions associated with the four portfolio classes are displayed in Figure 7. Consistent across all portfolio classes, the major components of the variance of (unexpected) portfolio excess returns are $\text{Var}\big(N_{i,\text{CF},t+1}\big)$, $\text{Var}\big(N_{i,\text{DR},t+1}\big)$, and $-2\text{Cov}\big(N_{i,\text{CF},t+1}, N_{i,\text{DR},t+1}\big)$. The remaining three terms that involve real interest rate news have a very marginal contribution, thus confirming the results for the market return decomposition above. In other words, real interest rate news represents a very marginal component of unexpected portfolio excess returns. In contrast with the variance decomposition for the market return, in the cases of the size and value portfolios, cash-flow news is the major component of unexpected portfolio returns, since $\text{Var}\big(N_{i,\text{CF},t+1}\big)$ is greater than $\text{Var}\big(N_{i,\text{DR},t+1}\big)$ for most deciles. The exceptions are the intermediate size deciles; BM deciles 6 and 9; and CP decile 5. Notice that for the last size decile (big stocks) the two components have a similar weight over the total return variance, thus confirming the results for the decomposition of the value-weighted market return, which is tilted toward large capitalization stocks. In sum, these results confirm the findings in Vuolteenaho (2002) showing that as we move from the aggregate to the individual level on equities, cash-flow news is the most important driver of total return variance, and hence the main component of (unexpected) excess returns.[19]

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[19] Eisdorfer (2007) also finds that for financially distressed stocks, cash-flow news is more important than discount rate news.

Panel A (S10)

Panel B (BM10)

Panel C (CP10)

Panel D (EP10)
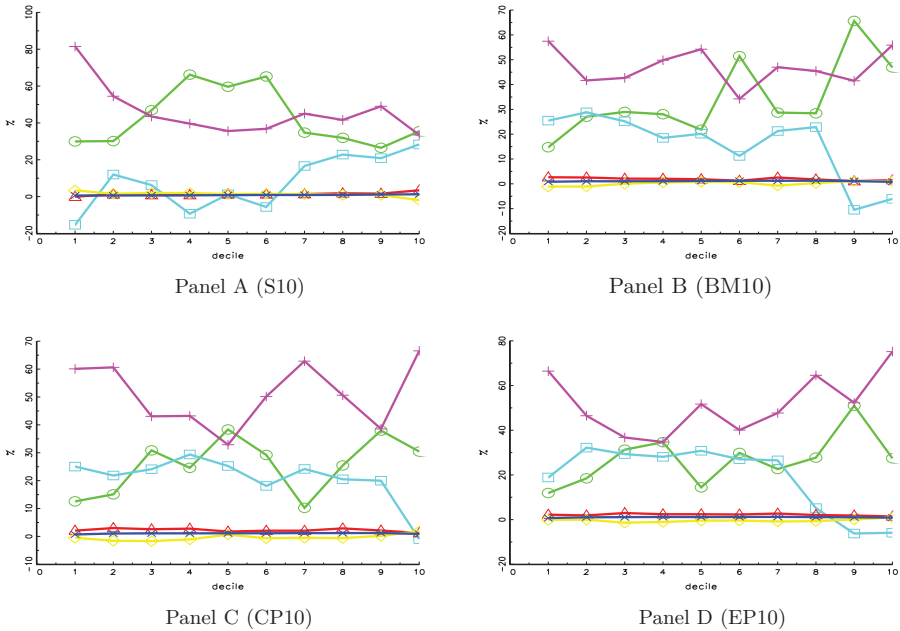
Figure 7. Variance decomposition for unexpected portfolio returns. This figure plots the variance decomposition for unexpected portfolio returns associated with the benchmark VAR presented in Section 4. The three components of portfolio returns are cash-flow news ($N_{i,\text{CF},t+1}$), discount rate news ($N_{i,\text{DR},t+1}$), and real interest rate news ($N_{i,\text{R},t+1}$). The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. $\text{Var}(N_{i,\text{DR}})$; $-2\text{Cov}(N_{i,\text{DR}}, N_{i,\text{CF}})$; $2\text{Cov}(N_{i,\text{DR}}, N_{i,\text{R}})$; $\text{Var}(N_{i,\text{CF}})$; $-2\text{Cov}(N_{i,\text{CF}}, N_{i,\text{R}})$; and $\text{Var}(N_{i,\text{R}})$ are represented by circles, squares, triangles, plus, diamonds, and stars, respectively. The sample is 1963:07–2008:06.

4.2 EXPLAINING THE RESPONSES TO MONETARY POLICY ACTIONS

Next, I estimate the responses of the components of portfolio excess returns to monetary policy actions. Following Bernanke and Kuttner (2005), the proxy for monetary policy is included in the VAR represented above as an exogenous variable,

$$\mathbf{x}_{i,t+1} = \mathbf{A}_i \mathbf{x}_{i,t} + \boldsymbol{\phi}_i \Delta \text{FFR}_{t+1} + \mathbf{u}_{i,t+1}, \tag{17}$$

and similarly for FFPREM. In order to estimate the contemporaneous response to monetary policy shocks, $\boldsymbol{\phi}_i$, I regress the residuals from the original VAR, $\epsilon_{i,t+1}$, on ΔFFR or FFPREM.[20] The effect of the FFR

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[20] The system of equations,

$$\epsilon_{i,t+1} = \mathbf{B}_{0i} + \boldsymbol{\phi}_i \Delta \text{FFR}_{t+1} + \mathbf{u}_{i,t+1},$$

is estimated by (equation-by-equation) OLS.

shock in current (unexpected) excess returns, discount rate news, real interest rate news, and cash-flow news for portfolio i, are then given, respectively, by

$$\eta_{i,r} \equiv \mathbf{e1}'\boldsymbol{\phi}_i, \tag{18}$$

$$\eta_{i,\mathrm{DR}} \equiv \mathbf{e1}'\rho\mathbf{A}_i(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i, \tag{19}$$

$$\eta_{i,\mathrm{R}} \equiv \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i, \tag{20}$$

$$\eta_{i,\mathrm{CF}} \equiv \mathbf{e1}'\boldsymbol{\phi}_i + \mathbf{e1}'\rho\mathbf{A}_i(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i + \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i$$
$$= (\mathbf{e1} + \mathbf{e2})'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i. \tag{21}$$

In the derivation of Equation (21), notice that

$$\mathbf{e1}'\boldsymbol{\phi}_i + \mathbf{e1}'\rho\mathbf{A}_i(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i + \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i$$
$$= [\mathbf{e1}'(\mathbf{I} - \rho\mathbf{A}_i) + \mathbf{e1}'\rho\mathbf{A}_i + \mathbf{e2}'](\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i$$
$$= (\mathbf{e1} + \mathbf{e2})'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i.$$

Note also that the effect on cash-flow news minus the effect on discount rate news and real interest rate news has to equalize the total effect on excess returns, according to the dynamic identity (10):

$$\eta_{i,\mathrm{CF}} - \eta_{i,\mathrm{DR}} - \eta_{i,\mathrm{R}} \equiv (\mathbf{e1} + \mathbf{e2})'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i - \mathbf{e1}'\rho\mathbf{A}_i(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i$$
$$- \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i = \mathbf{e1}'\boldsymbol{\phi}_i \equiv \eta_{i,r}.$$

To assess the statistical significance of the VAR-based return responses, $\eta_r, \eta_{\mathrm{DR}}, \eta_{\mathrm{R}}, \eta_{\mathrm{CF}}$, I compute individual empirical t-statistics, which are based on standard errors from a Bootstrap experiment. In this simulation, the VAR residuals are simulated 5,000 times, and the pseudo t-stats correspond to the original point estimates of the VAR-based responses divided by the empirical standard errors. The full details of this bootstrap experiment are provided in Appendix A.

First, I conduct the estimation for the excess market return. The point estimates for $\eta_r, \eta_{\mathrm{DR}}, \eta_{\mathrm{R}},$ and η_{CF} are $-1.06, -0.51, 0.19,$ and -1.38, respectively, when the monetary proxy is ΔFFR, whereas in the case of FFPREM the corresponding estimates are $-0.65, 0.01, 0.07,$ and -0.57, respectively.[21] Thus, the total market response to the FFR is almost

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[21] The effect on total returns is of slightly lower magnitude than in the simple regressions of Section 3 since in the VAR-based specification the dependent variable is the innovation in excess return and not the (total) excess market return. The use of the innovation in excess

entirely explained by a negative effect in aggregate cash-flow news, whereas the impact on the other two components of aggregate excess returns is much lower in magnitude.[22] These results differ partially to the results in Bernanke and Kuttner (2005), who obtain a large positive effect in future aggregate risk premia, which is larger in magnitude than the negative effect on future cash flows. The difference in results should be related with the different proxy for monetary policy, and the longer sample used in this article.[23] The negative estimate of η_{DR} is in line with previous evidence showing that an increase in the FFR (or in the Fed Discount rate) is associated with lower future excess market returns at several forecasting horizons (Jensen, Mercer, and Johnson, 1996; Patelis, 1997; Maio, 2012a, among others).

Figure 8 plots the responses of portfolio returns and its components to changes in the FFR. We can see that the estimates for η_R are very close to zero (slightly positive) and relatively flat across the different deciles, thus showing that the effect of ΔFFR on real interest rate news is marginal, and this pattern is robust across all the four portfolio classes.[24] On the other hand, η_{CF} is estimated negatively for all deciles among the four portfolio groups. Hence, an increase in the FFR is associated with a downward revision in future equity portfolio cash flows. In comparison, η_{DR} assumes negative estimates for most deciles within all portfolio classes. The exceptions are deciles 5 and 9 (CP10) and deciles 3 and 4 (EP10), in which the estimates for η_{DR} are positive. The empirical t-statistics associated with the estimated VAR responses show that the standard errors associated with η_{DR}

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returns comes from the fact that the VAR methodology relies on the return decomposition (Equation (10)), which is valid for unexpected returns rather than returns.

[22] Lin and Paravisini (2013) find that an increase in the financing constraints faced by firms lead to an increase in the volatility of cash flows.

[23] The sample used in Bernanke and Kuttner (2005) is 1973:01 to 2002:12. There is evidence showing that in recent years the variation in market returns is mostly attributable to cash-flow news in comparison to aggregate discount rate shocks (see, e.g., Maio, 2012b). Moreover, the evidence from Campbell, Giglio, and Polk (2012) indicates that the recent bear market (started in 2007) is mostly attributable to negative cash-flow news rather than positive shocks in market discount rates. By conducting the estimation for the 1973:01–2002:12 period, the estimates for η_r, η_{DR}, η_R, and η_{CF} are −1.03, 0.43, −0.04, and −0.64, respectively, when the monetary proxy is ΔFFR, whereas in the case of FFPREM the corresponding estimates are −0.59, 0.37, −0.01, and −0.23, respectively. Thus, I obtain large positive estimates for η_{DR} as in Bernanke and Kuttner (2005) (who obtain monthly estimates of 0.51 and −0.40 for η_{DR} and η_{CF}, respectively.)

[24] The estimates for η_R are very similar across different deciles and portfolio groups, thus showing that by using different VAR state vectors (with different excess returns) the resulting estimates of real interest rate news are relatively stable.

Figure 8. VAR-based portfolio return responses to shocks in ΔFFR. This figure plots the responses, and associated *t*-statistics, of unexpected portfolio returns ($\eta_{i,r}$); portfolio cash-flow news ($\eta_{i,CF}$); portfolio discount rate news ($\eta_{i,DR}$); and real interest rate news ($\eta_{i,R}$) to monetary policy shocks, as described in Section 4. The monetary policy proxy is ΔFFR, which is included as an exogenous variable in the benchmark VAR. The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. $\eta_{i,r}$, $\eta_{i,DR}$, $\eta_{i,R}$, and $\eta_{i,CF}$ are represented by circles, squares, triangles, and plus, respectively. The sample is 1963:07–2008:06.

are relatively large for several portfolios, while on the other hand, η_{CF} is estimated with high precision for the majority of the portfolios.

The VAR-based responses when the monetary proxy is FFPREM are displayed in Figure 9. Across the four portfolio classes, the estimates for η_{CF} are consistently negative. On the other hand, the point estimates for η_{DR} assume both negative and positive values within all portfolio groups, although in comparison to the results associated with ΔFFR the proportion of positive estimates increases significantly, particularly within EP10. However, most of these point estimates for η_{DR} are not statistically significant, whereas the estimates for η_{CF} are at least two standard errors away from zero for all deciles.

In sum, these results show that whereas η_{CF} is consistently negatively estimated across portfolios, the estimates for η_{DR} are less consistent in terms of sign. Consequently, the negative total portfolio return responses to monetary policy shocks (η_r) are associated with the negative effect on future portfolio dividends (cash flows). In most cases, this effect outweighs the negative impact of monetary policy actions on future portfolio excess returns. When η_{DR} assumes positive estimates, still it is the case that η_{CF} is the main driver for total portfolio responses.

These results are similar to those obtained for the market response to monetary policy actions, in the sense that the main driver of stock return responses is the negative effect on future cash flows, whereas the effect on future equity risk premia is less relevant. This finding sheds light on the monetary policy transmission mechanism across firms and is consistent with the evidence from Christiano, Eichenbaum, and Evans (1996). These results are also consistent with the evidence in Vuolteenaho (2002) that the main driver of variation in individual stock returns is cash-flow news rather than shocks in future stock discount rates, and thus, the impact of changes in monetary policy on individual stock (or portfolios of stocks) returns is more likely to work through future cash flows.

Another point of interest is to explain the dispersion of total responses across extreme deciles, documented in the previous section, as being matched by a corresponding dispersion in the monetary effect on cash-flow news or on discount rate news. The spreads in slopes across extreme deciles, and associated empirical t-stats, are presented in Table VI. Details on the bootstrapped t-stats are presented in Appendix A. In the case of S10, the dispersion, $\eta_{1,r} - \eta_{10,r} = -0.38$, is the result of a negative dispersion in η_{CF} (-1.83), which more than offsets the negative dispersion in η_{DR} (-1.44). In the cases of BM10, EP10, and CP10, the spreads, $\eta_{1,r} - \eta_{10,r}$, are equal to 0.82, 0.77, and 0.61, respectively. These spreads are matched by corresponding gaps, $\eta_{1,CF} - \eta_{10,CF}$, of 1.57, 2.12, and 2.30, which outweigh the positive

Panel A (S10)

Panel B (BM10)

Panel C (CP10)

Panel D (EP10)

Panel E (S10, t-stats)

Panel F (BM10, t-stats)

Panel G (CP10, t-stats)
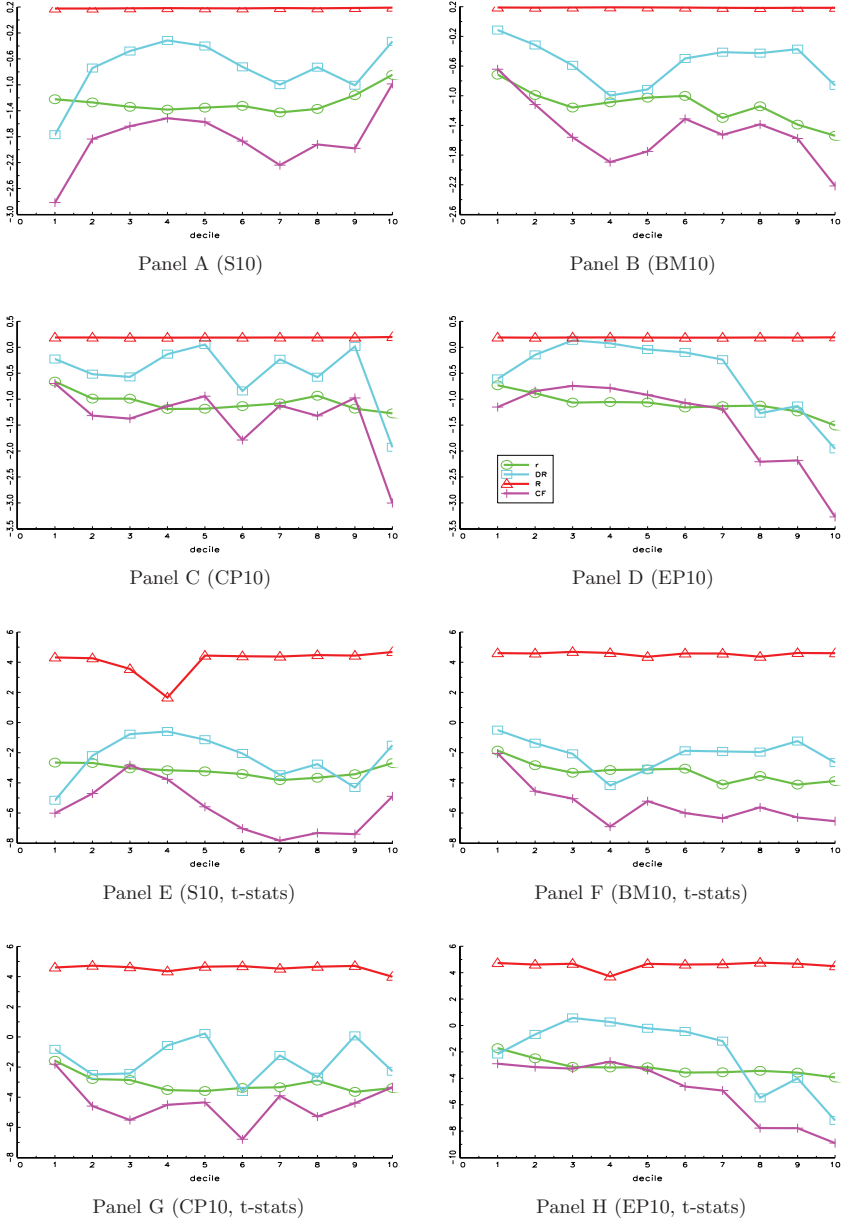
Panel H (EP10, t-stats)
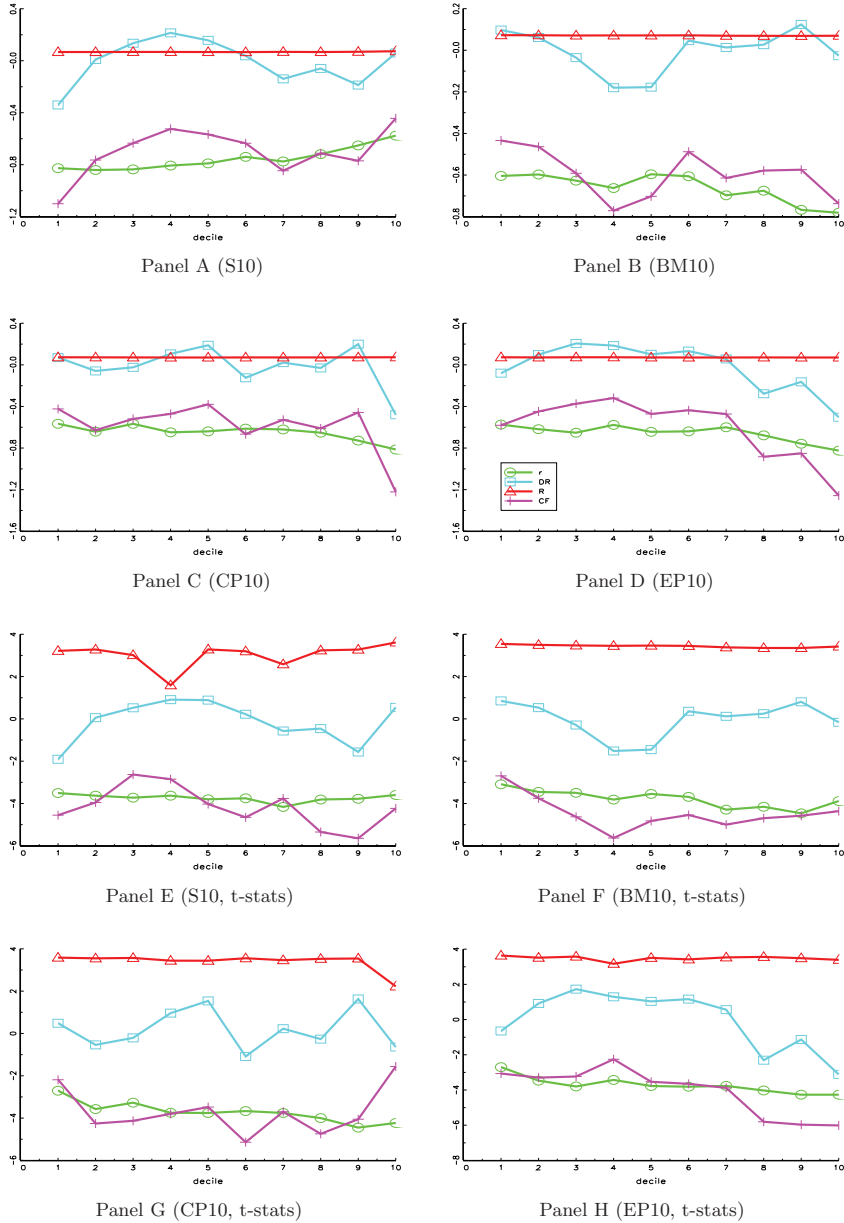
Figure 9. VAR-based portfolio return responses to shocks in FFPREM. This figure plots the responses, and associated *t*-statistics, of unexpected portfolio returns ($\eta_{i,r}$); portfolio cash-flow news ($\eta_{i,CF}$); portfolio discount rate news ($\eta_{i,DR}$); and real interest rate news ($\eta_{i,R}$) to monetary policy shocks, as described in Section 4. The monetary policy proxy is FFPREM, which is included as an exogenous variable in the benchmark VAR. The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. $\eta_{i,r}$, $\eta_{i,DR}$, $\eta_{i,R}$, and $\eta_{i,CF}$ are represented by circles, squares, triangles, and plus, respectively. The sample is 1963:07–2008:06.

Table VI. Spreads in VAR-based responses

This table presents the spreads (first decile minus last decile) in the responses, and associated *t*-statistics (in parenthesis), of unexpected portfolio returns ($\eta_{1,r} - \eta_{10,r}$); portfolio cash-flow news ($\eta_{1,CF} - \eta_{10,CF}$); portfolio discount rate news ($\eta_{1,DR} - \eta_{10,DR}$); and real interest rate news ($\eta_{1,R} - \eta_{10,R}$) to monetary policy actions. The monetary policy proxies are ΔFFR and FFPREM, which are included as exogenous variables in the benchmark VAR presented in Section 4. The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. The sample is 1963:07–2008:06. The *t*-statistics are obtained from a bootstrap simulation.

	$\eta_{1,r} - \eta_{10,r}$	$\eta_{1,DR} - \eta_{10,DR}$	$\eta_{1,R} - \eta_{10,R}$	$\eta_{1,CF} - \eta_{10,CF}$
Panel A (ΔFFR)				
S10	−0.38	−1.44	−0.01	−1.83
	(−0.68)	(−3.55)	(−0.24)	(−3.60)
BM10	0.82	0.75	0.00	1.57
	(1.48)	(1.90)	(0.08)	(3.34)
CP10	0.61	1.70	−0.01	2.30
	(1.07)	(1.91)	(−0.13)	(2.36)
EP10	0.77	1.35	−0.00	2.12
	(1.35)	(3.49)	(−0.05)	(3.87)
Panel B (FFPREM)				
S10	−0.25	−0.40	−0.01	−0.66
	(−0.88)	(−1.94)	(−0.20)	(−2.48)
BM10	0.18	0.12	0.00	0.30
	(0.63)	(0.62)	(0.10)	(1.29)
CP10	0.25	0.55	0.00	0.80
	(0.87)	(0.72)	(0.01)	(0.99)
EP10	0.25	0.42	0.00	0.68
	(0.87)	(2.10)	(0.07)	(2.41)

spreads in η_{DR} of 0.75, 1.35, and 1.70, respectively. The estimates associated with $\eta_{1,CF} - \eta_{10,CF}$ are more than two standard errors away from zero for all four portfolio groups, whereas the corresponding estimates for $\eta_{1,r} - \eta_{10,r}$ and $\eta_{1,DR} - \eta_{10,DR}$ (in the cases of BM10 and CP10) are <2 standard errors from 0. Thus, the spreads in $\eta_{i,CF}$ are more precisely estimated than the spreads in both $\eta_{i,r}$ and $\eta_{i,DR}$. In sum, these results show that small (value) stocks have a greater response to monetary policy actions than large (growth) stocks due to the relative greater impact (in magnitude) of the FFR on the future cash flows of these stocks.

When the monetary proxy is FFPREM the results are not substantially different. The dispersion, $\eta_{1,r} - \eta_{10,r}$, associated with the size portfolios is −0.25, which is matched by a negative dispersion in η_{CF} (−0.66) that outweighs the negative dispersion in η_{DR} (−0.40). Regarding the value portfolios, the spreads, $\eta_{1,r} - \eta_{10,r}$, are equal to 0.18, 0.25, and 0.25 for BM10,

EP10, and CP10, respectively. These gaps are explained by positive spreads, $\eta_{1,\text{CF}} - \eta_{10,\text{CF}}$, of 0.30, 0.68, and 0.80, respectively, which more than offset the positive spreads in η_{DR} of 0.12, 0.42, and 0.55, respectively. The empirical t-ratios associated with $\eta_{1,\text{CF}} - \eta_{10,\text{CF}}$ are above two in absolute value in the estimation with S10 and EP10, whereas in the cases of BM10 and CP10 the standard errors are relatively large. Overall, these results indicate that the dispersion in return responses to changes in FFPREM across opposite deciles is explained by a similar dispersion in the responses of cash-flow news, and this pattern is reasonably consistent among all portfolio groups.

5. Sensitivity Analysis

In this section, I conduct several robustness checks to the VAR identification conducted in the last section. First, I use an alternative VAR specification in which the specific portfolio dividend-to-price ratio replaces the aggregate dividend-to-price ratio. Second, I conduct a subsample analysis. Third, I estimate a higher order VAR to obtain the betas against monetary actions. Fourth, I use an alternative measure of portfolio dividends in constructing the dividend yield. Finally, I conduct an alternative identification of the components of portfolio (unexpected) excess returns.

5.1 ALTERNATIVE VAR SPECIFICATION

The benchmark VAR specification used in the previous section uses the market dividend-to-price ratio as one of the variables that helps to forecast expected (excess) portfolio returns, and thus, that allows to identify portfolio discount rate news. However, to be consistent with the Campbell and Shiller (1988a) dynamic present-value relation, it is the portfolio's dividend-to-price ratio, rather than the market dividend-to-price ratio, that should help to forecast future expected excess returns for that given portfolio,

$$d_{i,t} - p_{i,t} = \text{const.} + \text{E}_t \sum_{j=0}^{\infty} \rho^j \left(r_{i,t+1+j} - \Delta d_{i,t+1+j} \right), \tag{22}$$

where $d_{i,t} - p_{i,t}$ denotes the log dividend-to-price ratio for portfolio i. Thus, I use the portfolio's log dividend yield in the VAR state vector:

$$\mathbf{x}_{it} \equiv \left[r_{\text{r},t}, \Delta r_{\text{f},t}, \text{RREL}_t, \text{TERM}_t, d_{i,t} - p_{i,t}, r_{i,t} \right]', i = 1, \ldots, 10. \tag{23}$$

This VAR specification is denoted as VAR I.

I repeat the analysis of the previous section for the S10, BM10, CP10, and EP10 portfolio groups. Results presented in the internet appendix show that the R^2 estimates associated with the excess return equation in the case of the size portfolios are significantly larger for the first two deciles (over 10% for the first decile), whereas for the remaining deciles there is a significant decline in the explanatory ratios, almost in a monotonic way. In the case of the BM10, CP10, and EP10 portfolios, there is an approximate u-shaped pattern for the R^2 estimates, that is, the explanatory ratios are larger for the first and last deciles, and assume lower values for the intermediate deciles.

Results presented in the appendix also show that the main driver of equity returns across the four portfolio groups is cash-flow news. Specifically, for all portfolios we have $\text{Var}(N_{i,\text{CF},t+1}) > \text{Var}(N_{i,\text{DR},t+1})$ and the weights associated with $\text{Var}(N_{i,\text{CF},t+1})$ are $>100\%$, which implies that the covariances terms between the two return components are negative.

Figure 10 plots the responses of portfolio returns and the respective components to changes in the FFR in the case of VAR I. Similarly to the benchmark VAR, the effect of ΔFFR on real interest rate news is marginal and relatively flat across the different deciles. On the other hand, the estimates for η_{CF} are consistently negative for all deciles within the four portfolio groups. In comparison, the estimates for η_{DR} are also consistently negative across all portfolios, although with lower magnitudes than η_{CF}. We can see that the estimates for both η_{CF} and η_{DR} are strongly statistically significant, as indicated by the respective empirical t-statistics, which are above 3 (in magnitude). Thus, the inclusion of the portfolio dividend-to-price ratio (rather than the market dividend-to-price ratio) in the VAR, leads to better estimates of portfolio cash flow and discount rate news, and thus more precise estimates of η_{CF} and η_{DR}. Overall, the negative total portfolio return responses are a result of the negative effect of ΔFFR on future portfolio dividend changes, which compensates the negative impact of the FFR on future portfolio risk premia, similarly to the results obtained for the benchmark VAR.

The responses of portfolio returns and the respective components to the alternative monetary proxy, FFPREM, are displayed in Figure 11. The results are very similar to the results associated with ΔFFR. Specifically, the point estimates for η_{CF} are negative in all deciles and portfolio groups, and this also holds for η_{DR}, although with lower magnitudes. The empirical t-stats indicate that both η_{CF} and η_{DR} are more than three standard deviations away from zero across all deciles.

Results presented in the internet appendix show that the spread in total responses to ΔFFR between small and large stocks ($\eta_{1,\text{r}} - \eta_{10,\text{r}}$) is -0.34,

Panel A (S10)

Panel B (BM10)

Panel C (CP10)

Panel D (EP10)

Panel E (S10, t-stats)

Panel F (BM10, t-stats)

Panel G (CP10, t-stats)

Panel H (EP10, t-stats)

Figure 10. VAR-based portfolio return responses to shocks in ΔFFR (VAR I). This figure plots the responses, and associated *t*-statistics, of unexpected portfolio returns ($\eta_{i,\mathrm{r}}$); portfolio cash-flow news ($\eta_{i,\mathrm{CF}}$); portfolio discount rate news ($\eta_{i,\mathrm{DR}}$); and real interest rate news ($\eta_{i,\mathrm{R}}$) to monetary policy shocks, as described in Section 5. The monetary policy proxy is ΔFFR, which is included as an exogenous variable in VAR I. The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. $\eta_{i,\mathrm{r}}$, $\eta_{i,\mathrm{DR}}$, $\eta_{i,\mathrm{R}}$, and $\eta_{i,\mathrm{CF}}$ are represented by circles, squares, triangles, and plus, respectively. The sample is 1963:07–2008:06.

Panel A (S10)

Panel B (BM10)

Panel C (CP10)

Panel D (EP10)

Panel E (S10, t-stats)

Panel F (BM10, t-stats)
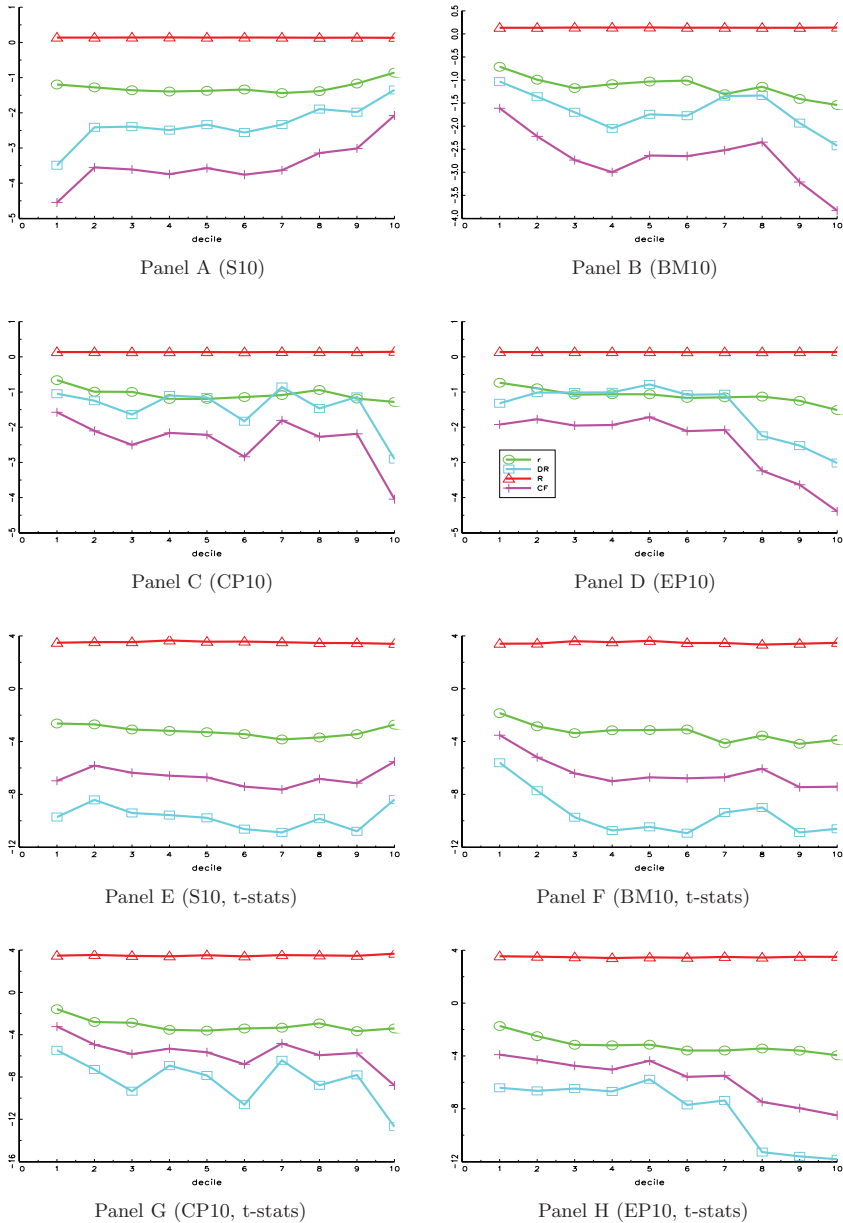
Panel G (CP10, t-stats)

Panel H (EP10, t-stats)

Figure 11. VAR-based portfolio return responses to shocks in FFPREM (VAR I). This figure plots the responses, and associated *t*-statistics, of unexpected portfolio returns ($\eta_{i,\mathrm{r}}$); portfolio cash-flow news ($\eta_{i,\mathrm{CF}}$); portfolio discount rate news ($\eta_{i,\mathrm{DR}}$); and real interest rate news ($\eta_{i,\mathrm{R}}$) to monetary policy shocks, as described in Section 5. The monetary policy proxy is FFPREM, which is included as an exogenous variable in VAR I. The analysis is conducted for portfolio groups S10, BM10, CP10, and EP10. $\eta_{i,\mathrm{r}}$, $\eta_{i,\mathrm{DR}}$, $\eta_{i,\mathrm{R}}$, and $\eta_{i,\mathrm{CF}}$ are represented by circles, squares, triangles, and plus, respectively. The sample is 1963:07–2008:06.
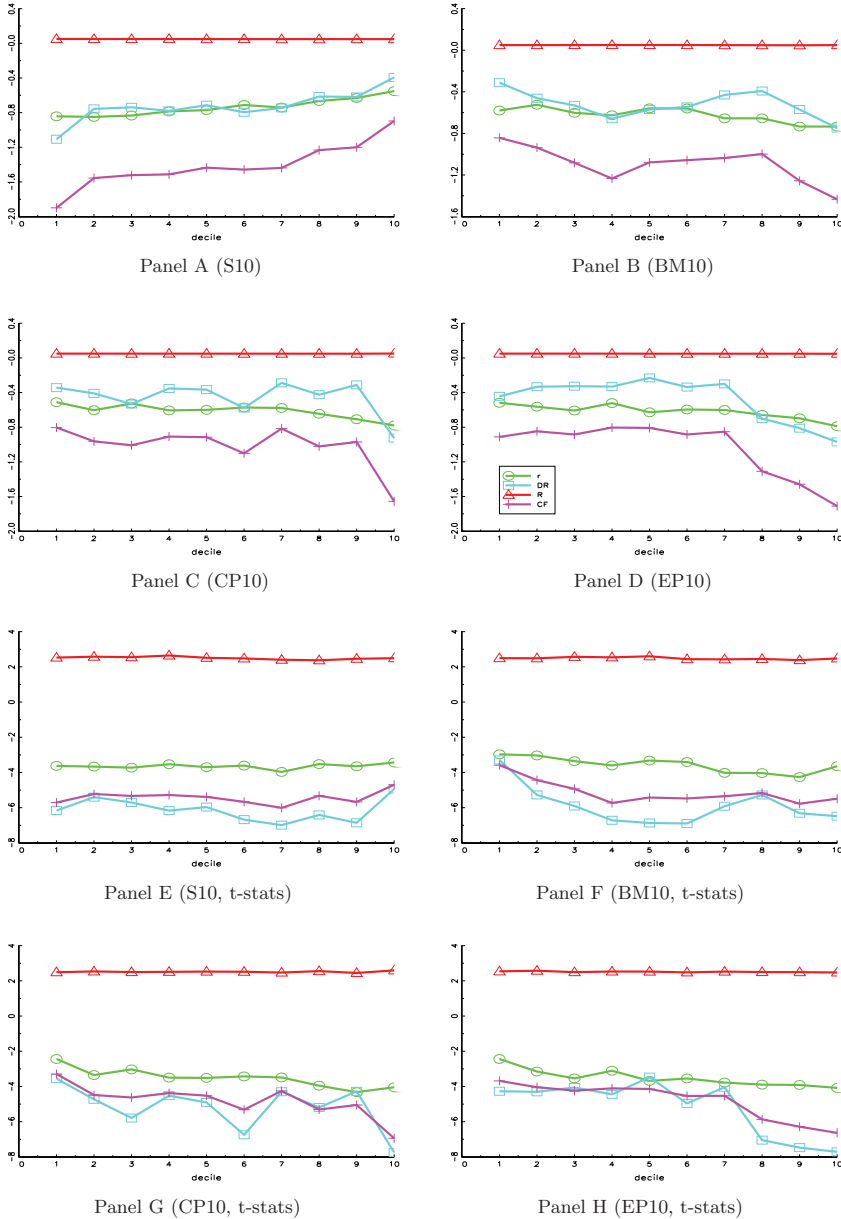
which can be explained by a spread, $\eta_{1,\mathrm{CF}} - \eta_{10,\mathrm{CF}}$, of -2.47 that outweighs a corresponding negative spread in η_{DR} (-2.14). In the case of the growth-value portfolios, BM10, EP10, and CP10, the gaps, $\eta_{1,\mathrm{r}} - \eta_{10,\mathrm{r}}$, are 0.83, 0.77, and 0.62, respectively. These spreads are explained by positive gaps, $\eta_{1,\mathrm{CF}} - \eta_{10,\mathrm{CF}}$, of 2.22, 2.47, and 2.47 for BM10, EP10, and CP10, respectively, which offset the positive spreads associated with η_{DR} (1.39, 1.70, and 1.86, respectively). The estimates for both $\eta_{1,\mathrm{CF}} - \eta_{10,\mathrm{CF}}$ and $\eta_{1,\mathrm{DR}} - \eta_{10,\mathrm{DR}}$ are more than two standard errors away from zero in all cases, whereas there is no statistical significance for the spread in total responses, $\eta_{1,\mathrm{r}} - \eta_{10,\mathrm{r}}$.

Therefore, as in the case of the benchmark VAR, small (value) stocks are more responsive than large (growth) to ΔFFR due to a stronger effect on future cash flows. When the monetary proxy is FFPREM, the decomposition of the dispersion in η_{r} between η_{CF} and η_{DR} is qualitatively similar to the case of ΔFFR, among the four portfolio groups.

5.2 SUBSAMPLE ANALYSIS

I estimate the VAR-based responses (from both the benchmark VAR and VAR I) for the 1983:01–2008:06 period, using the VAR dynamics estimated over the full sample, to assess the stability of the results shown above. Results presented in the internet appendix show that, for both VAR specifications, the negative effect of ΔFFR on portfolio excess returns are explained by negative point estimates associated with η_{CF}, which outweighs negative estimates (with lower magnitudes) associated with η_{DR}. When the monetary proxy is FFPREM, a similar pattern holds for the size deciles and the value portfolios (higher deciles) associated with BM10, CP10, and EP10, although the relation is less clear for growth portfolios. However, these results should be interpreted with some caution given that the estimates of the VAR-implied return responses are based on the VAR dynamics estimated over a longer period.

5.3 HIGHER ORDER VAR

I estimate both the benchmark VAR and VAR I by using three lags, the optimal order according to the Bayesian Information Criterion (BIC) for all portfolios.[25] The objective is to assess whether allowing for a more complex dynamic structure in the VAR leads to qualitatively different portfolio responses to monetary policy actions. With a higher order VAR, all the VAR

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[25] I thank the referee for suggesting this analysis.

formulas presented in Section 4 remain valid if one augments the VAR state vector by including the lagged variables and interprets **A** as the VAR companion matrix. Details are presented in Appendix B below.

Results displayed in the internet appendix indicate that the negative return responses to monetary policy actions across all portfolios are the result of negative effects on portfolio cash-flow news that outweighs the effects on portfolio discount rate news, which assume negative values with lower magnitudes or slightly positive values for some portfolios. Moreover, the estimates of η_{CF} are statistically significant for most portfolios as indicated by the empirical t-ratios. These results are robust across VAR specifications (Benchmark VAR and VAR I) and for both monetary policy proxies.

5.4 ALTERNATIVE MEASURE OF PORTFOLIO DIVIDENDS

In the estimation of VAR I above, I use monthly portfolio dividends with reinvestment at the portfolio monthly rate of return. This measure of dividends is entirely consistent with the Campbell and Shiller (1988a) present-value relation (Cochrane, 2008). However, as a robustness check and following most of the predictability literature, I use an alternative measure in which monthly dividends are summed over the previous 1 year without reinvestment. This removes the seasonality pattern in monthly dividends. Details are presented in Appendix C.

The results displayed in the internet appendix show that the estimates for η_{CF} are negative across all portfolios, and in most cases, more than two standard errors away from zero. The sole exception is decile 9 within BM10 in which the estimate is not statistically significant. The estimates associated with η_{DR} assume negative values in most cases, although in the case of the size portfolios, and using FFPREM as monetary proxy, most estimates are positive but not statistically significant. Overall, as in the case of the baseline specification of VAR I above, the negative portfolio return responses to monetary policy actions come from a negative effect in future cash flows rather than from an effect on future discount rates.

5.5 ALTERNATIVE IDENTIFICATION OF PORTFOLIO RETURN COMPONENTS

In the identification pursued in both the benchmark VAR and VAR I above, I follow the traditional approach in the literature in which discount rate news is directly identified from the VAR, and cash-flow news is pinned down as the residual from stock returns. However, there has been some criticism about this methodology. For example, Chen and Zhao (2009)

argue that any misspecification in the predictability of aggregate returns (that directly affects discount rate news) will translate indirectly into cash-flow news (being the residual component). Moreover, by treating cash-flow news as the residual, this return component might be overstated. On the other hand, Campbell, Polk, and Vuolteenaho (2010) and Engsted, Pedersen, and Tanggaard (2012) argue that with a properly specified VAR, the two identification approaches are equivalent, and hence, should yield similar results.

As a robustness check to the results shown above, I conduct an alternative identification in which the components of portfolio excess returns are identified in the following way,

$$N_{i,\mathrm{CF},t+1} \equiv (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{i,t+1+j} = \mathbf{e3}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\epsilon}_{i,t+1} = \boldsymbol{\lambda}_i'\boldsymbol{\epsilon}_{i,t+1} \quad (24)$$

$$N_{\mathrm{R},t+1} \equiv (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j r_{\mathrm{r},t+1+j} = \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\epsilon}_{i,t+1} = \boldsymbol{\psi}_i'\boldsymbol{\epsilon}_{i,t+1}, \quad (25)$$

$$N_{i,\mathrm{DR},t+1} \equiv (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{i,t+1+j} = N_{i,\mathrm{CF},t+1} - N_{\mathrm{R},t+1} - [r_{i,t+1} - \mathrm{E}_t(r_{i,t+1})]$$

$$= \big[\mathbf{e3}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1} - \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1} - \mathbf{e1}'\big]\boldsymbol{\epsilon}_{i,t+1} = \big(\boldsymbol{\lambda}_i - \boldsymbol{\psi}_i - \mathbf{e1}\big)'\boldsymbol{\epsilon}_{i,t+1}, i = 1, \ldots, 10,$$

$$(26)$$

where **e3** is an indicator vector that takes a value of one in the cell corresponding to the position of dividend growth in the VAR. Under this identification, dividend/cash-flow news is estimated directly, and discount rate news is identified as the residual component of (unexpected) current excess returns. However, both this identification and the identifications pursued in both the benchmark VAR and VAR I are based on the Campbell (1991) dynamic identity for returns.

The VAR state vector is now given by

$$\mathbf{x}_{i,t} \equiv \big[r_{\mathrm{r},t}, \Delta r_{\mathrm{f},t}, \mathrm{RREL}_t, \Delta d_{i,t}, d_{i,t} - p_{i,t}, r_{i,t}\big]', i = 1, \ldots, 10, \quad (27)$$

which is denoted as VAR II. The inclusion of the log portfolio dividend growth, $\Delta d_{i,t}$, is needed in order to identify dividend/cash-flow news. The excess portfolio return is still necessary in the VAR to obtain discount rate news as the residual component of equity excess returns. The portfolio dividend-to-price ratio is a valid predictor of dividend growth (as well as

for risk premia) according to Equation (22).[26] As in the benchmark VAR, the real interest rate is necessary in order to identify interest rate news. Δr_f and RREL are kept in the VAR to help estimate interest rate news.

Since the algebraic expressions for cash flow and discount rate news are different than in the benchmark identification, it follows that the estimated responses of cash flow and discount rate news to monetary shocks are now given by

$$\eta_{i,\mathrm{CF}} \equiv \mathbf{e3}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i, \tag{28}$$

$$\begin{aligned} \eta_{i,\mathrm{DR}} &\equiv \mathbf{e3}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i - \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1}\boldsymbol{\phi}_i - \mathbf{e1}'\boldsymbol{\phi}_i \\ &= \left[\mathbf{e3}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1} - \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A}_i)^{-1} - \mathbf{e1}'\right]\boldsymbol{\phi}_i. \end{aligned} \tag{29}$$

VAR II is estimated for each decile across the four portfolio sets. Results provided in the internet appendix results show that the R^2 estimates for the portfolio dividend growth equations are above 30% for all portfolio groups. These estimates are substantially larger than the corresponding R^2 estimates associated with excess returns in both the benchmark VAR and VAR I specifications, which is in part explained by the significant forecasting power of portfolio dividend yields for future portfolio dividend growth. Hence, these results provide evidence that, at the portfolio level and using monthly reinvested dividends, it is easier to forecast dividend growth than risk premia. This is partially consistent with the evidence at the aggregate level found in Binsbergen and Koijen (2010) and Ang (2012), and in contrast to the results obtained (at the annual frequency) in Cochrane (2008, 2011) and Chen (2009), among others. Regarding the size portfolios, the predictability of dividend growth for large stocks is significantly larger than for small stocks (forecasting ratio of 52.19% for the 10th decile versus 30.38% for the first decile). In the case of the BM10 portfolios, the R^2 estimates are slightly larger for growth stocks than for value stocks (50.80% for the first decile versus 44.07% for the last decile). This pattern is also present in the case of CP10 and EP10, although for these groups the intermediate deciles have the greatest explanatory ratios (above 50%).

Despite the different identification, it turns out that cash-flow news is still the main driver of portfolio (unexpected) returns, as in VAR I, with $\mathrm{Var}(N_{i,\mathrm{CF},t+1}) > \mathrm{Var}(N_{i,\mathrm{DR},t+1})$ holding for all portfolios. Specifically, the weights associated with $\mathrm{Var}(N_{i,\mathrm{CF},t+1})$ are $>100\%$ for all portfolios, with the

---

[26] Cochrane (1992, 2008, 2011), Lettau and Ludvigson (2005), Chen (2009), among others, discuss the predictive role of the aggregate dividend-to-price ratio for aggregate dividend growth.

sole exception of the first decile associated with EP10. In contrast, the weights associated with $\mathrm{Var}(N_{i,\,\mathrm{DR},\,t+1})$ are $<40\%$ for most portfolios.

Results displayed in the internet appendix show that, similarly to VAR I, η_{CF} assumes negative estimates for all portfolios, whereas the estimates associated with η_{DR} are also negative, but with lower magnitudes. The estimates for both η_{CF} and η_{DR} are strongly significant as indicated by the empirical t-stats. When one uses FFPREM as monetary policy measure, the results are qualitatively similar to those associated with ΔFFR. Therefore, by using an alternative identification of cash flow and discount rate news it is still the case that the negative total portfolio return responses are a consequence of the negative effect of monetary shocks on future portfolio dividend changes, which dominates the effect on future equity risk premia.

6. Conclusion

In this article, I analyze the effect of monetary policy actions on the cross-section of equity returns. Based on earlier theoretical work for the monetary transmission mechanism, one can argue that changes in monetary policy should produce differentiated effects on firms and stocks with different characteristics (e.g., size, book-to-market ratio).

The results show that the impact of monthly changes in the FFR is significantly greater for the returns of small relative to big stocks. Moreover, by using three different classes of portfolios sorted on fundamentals-to-price ratios the results show that value stocks are more responsive to monetary shocks than growth stocks. In sum, more financially constrained stocks are more responsive to increases in the FFR than less financially constrained stocks.

More importantly, by using a VAR methodology the results indicate that the negative effect of FFR changes on stock returns comes from a corresponding negative effect on future expected cash flows (cash-flow news), which is stronger than the impact on future equity risk premia (discount rate news). Thus, cash-flow news is the main return component affected by changes in the FFR. Moreover, I find that the dispersion in return responses to monetary shocks across stocks is explained by a similar dispersion in the effects into cash-flow news, which outweighs the dispersion in discount rate news betas. These results are reasonably robust to different VAR specifications. Thus, in general, the stronger response in the returns of more financially constrained stocks to shocks in monetary policy is largely attributable to the stronger effect of these shocks in the revisions of future equity

cash flows. Therefore, these results represent new evidence on the effect of monetary policy on stock prices and on the monetary transmission mechanism.

Appendix A: Bootstrap Algorithm

The bootstrap algorithm associated with the VAR-based responses to monetary policy actions consists of the following steps:

(1) The first-order VAR,

$$\mathbf{x}_{i,t+1} = \mathbf{A}_i \mathbf{x}_{i,t} + \epsilon_{i,t+1}, i = 1, \ldots, 10, \tag{A.1}$$

is estimated for the original sample and one saves the estimated VAR coefficient matrix, $\widehat{\mathbf{A}}_i$, and the vector of VAR residuals, $\widehat{\epsilon}_{i,t+1}$.

(2) In each replication $b = 1, \ldots, 5,000$, I draw with replacement from the VAR residuals,

$$\{\widehat{\epsilon}^b_{i,t+1}\}, t = s^b_{i,1}, s^b_{i,2}, \ldots, s^b_{i,T}, \tag{A.2}$$

where the time indices $s^b_{i,1}, s^b_{i,2}, \ldots, s^b_{i,T}$ are created randomly from the original time sequence $1, \ldots, T$. Notice that the residuals for all the equations in the VAR have the same time sequence in order to account for their contemporaneous cross-correlation. I also simulate (independently from the VAR residuals) the monetary proxy (e.g., ΔFFR),

$$\{\Delta\text{FFR}^b_{t+1}\}, t = r^b_1, r^b_2, \ldots, r^b_T, \tag{A.3}$$

where the time indices $r^b_1, r^b_2, \ldots, r^b_T$ are created randomly from the original time sequence $1, \ldots, T$.

(3) For each replication $b = 1, \ldots, 5,000$, I construct a pseudo sample of the VAR state variables by imposing recursively the VAR equations:

$$\mathbf{x}^b_{i,t+1} = \widehat{\mathbf{A}}_i \mathbf{x}^b_{it} + \widehat{\epsilon}^b_{i,t+1}. \tag{A.4}$$

(4) In each replication, I estimate the VAR(1), but using the artificial data rather than the original data,

$$\mathbf{x}^b_{i,t+1} = \mathbf{A}^b_i \mathbf{x}^b_{i,t} + \mathbf{v}^b_{i,t+1}, \tag{A.5}$$

and the associated artificial residuals are regressed on the artificial monetary proxy,

$$\mathbf{v}^b_{i,t+1} = \mathbf{B}^b_{0i} + \phi^b_i \Delta\text{FFR}^b_{t+1} + \mathbf{u}^b_{i,t+1}, \tag{A.6}$$

where the superscript b is to clarify that all variables and parameters are associated with simulation b th. It follows that the return (and respective components) responses are given by

$$\eta_{i,\mathrm{r}}^{b} \equiv \mathbf{e1}'\boldsymbol{\phi}_{i}^{b}, \tag{A.7}$$

$$\eta_{i,\mathrm{DR}}^{b} \equiv \mathbf{e1}'\rho\mathbf{A}_{i}^{b}\big(\mathbf{I} - \rho\mathbf{A}_{i}^{b}\big)^{-1}\boldsymbol{\phi}_{i}^{b}, \tag{A.8}$$

$$\eta_{i,\mathrm{R}}^{b} \equiv \mathbf{e2}'\big(\mathbf{I} - \rho\mathbf{A}_{i}^{b}\big)^{-1}\boldsymbol{\phi}_{i}^{b}, \tag{A.9}$$

$$\eta_{i,\mathrm{CF}}^{b} \equiv (\mathbf{e1} + \mathbf{e2})'\big(\mathbf{I} - \rho\mathbf{A}_{i}^{b}\big)^{-1}\boldsymbol{\phi}_{i}^{b}. \tag{A.10}$$

I also compute the spreads in responses across extreme deciles within each portfolio class, $s_{j}^{b} \equiv \eta_{1,j}^{b} - \eta_{10,j}^{b}, j \equiv \mathrm{r}, \mathrm{DR}, \mathrm{R}, \mathrm{CF}$.

(5) Given the collection of 5,000 estimates for the responses, $(\eta_{i,\mathrm{r}}^{b}, \eta_{i,\mathrm{DR}}^{b}, \eta_{i,\mathrm{R}}^{b}, \eta_{i,\mathrm{CF}}^{b}), b = 1, \ldots, 5,000$, I construct an empirical standard error. For example, in the case of $\eta_{i,\mathrm{CF}}$ we have

$$\mathrm{se}(\eta_{i,\mathrm{CF}}) = \sqrt{\frac{1}{5,000} \sum_{b=1}^{5,000} (\eta_{i,\mathrm{CF}}^{b} - \bar{\eta}_{i,\mathrm{CF}})^{2}}, \tag{A.11}$$

where $\bar{\eta}_{i,\mathrm{CF}} = \frac{1}{5,000}\sum_{b=1}^{5,000} \eta_{i,\mathrm{CF}}^{b}$ denotes the mean across all pseudo samples. The corresponding pseudo t-ratio is then calculated as

$$t(\eta_{i,\mathrm{CF}}) = \frac{\eta_{i,\mathrm{CF}}}{\mathrm{se}(\eta_{i,\mathrm{CF}})}, \tag{A.12}$$

where $\eta_{i,\mathrm{CF}}$ denotes the cash flow response computed from the original sample. In the case of the spread in responses associated with cash-flow news, the empirical t-stat is constructed as

$$t(s_{\mathrm{CF}}) = \frac{s_{\mathrm{CF}}}{\mathrm{se}(s_{\mathrm{CF}})}, \tag{A.13}$$

where s_{CF} denotes the estimate for the orginal sample and $\mathrm{se}(s_{\mathrm{CF}})$ represents the respective standard error calculated as

$$\mathrm{se}(s_{\mathrm{CF}}) = \sqrt{\frac{1}{5,000} \sum_{b=1}^{5,000} (s_{\mathrm{CF}}^{b} - \bar{s}_{\mathrm{CF}})^{2}}, \tag{A.14}$$

with $\bar{s}_{\mathrm{CF}}$ denoting the mean across pseudo samples.

Appendix B: Higher Order VAR

To simplify notation consider a simplified VAR state vector that includes only RREL and the portfolio return, $\mathbf{x}_{i,t} \equiv \left[RREL_t, r_{i,t} \right]'$, and assume a two-order VAR:

$$
\mathbf{x}_{i,t+1} = \mathbf{A}_{1i}\mathbf{x}_{i,t} + \mathbf{A}_{2i}\mathbf{x}_{i,t-1} + \epsilon_{i,t+1} \Leftrightarrow \begin{bmatrix} RREL_{t+1} \\ r_{i,t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} RREL_t \\ r_{i,t} \end{bmatrix}
$$
$$
+ \begin{bmatrix} a_{13} & a_{14} \\ a_{23} & a_{24} \end{bmatrix} \begin{bmatrix} RREL_{t-1} \\ r_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \end{bmatrix}.
$$

(B.15)

Following Campbell and Shiller (1988a), by redefining the VAR state vector to include the lagged variables, the two-order VAR can be redefined as a VAR(1),

$$
\begin{bmatrix} RREL_{t+1} \\ r_{i,t+1} \\ RREL_t \\ r_{i,t} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} RREL_t \\ r_{i,t} \\ RREL_{t-1} \\ r_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ 0 \\ 0 \end{bmatrix}
$$

(B.16)

$$
\Leftrightarrow \mathbf{z}_{i,t+1} = \mathbf{A}_i \mathbf{z}_{it} + \mathbf{e}_{i,t+1},
$$

where $\mathbf{A}_i$ denotes the VAR companion matrix and $\mathbf{e}_i$ represents the vector of residuals in the new VAR.

Appendix C: Alternative Measure of Portfolio Dividends

To obtain monthly series of portfolio dividends without reinvestment, I follow an approach similar to Hodrick (1992). Using the same notation as in Section 2, I obtain a normalized series of the price level for each portfolio,

$$
P_{i,t+1} = P_{i,t} R^*_{i,t+1}, \tag{C.17}
$$

where $P_{i,t}$ is set to one at the beginning of the sample (1926:06 for both S10 and BM10, and 1951:06 for both CP10 and EP10). Then, the monthly dividend is given by

$$
D_{i,t+1} = (R_{i,t+1} - R^*_{i,t+1})P_{i,t}. \tag{C.18}
$$

Finally, the annualized dividend at month $t+1$ without reinvestment is

$$D_{i,\,t+1}^{12} = \sum_{j=0}^{11} D_{i,\,t+1-j}. \tag{C.19}$$

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