Online Appendix:

Show Me the Money: The Monetary Policy Risk Premium*

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I Individual Returns, Market Return, and Failure of CAPM

Here, we provide a simple example where the processes for the firm's returns, dR_i, and the aggregate market return, dR^*, in Appendices A.2 and A.3 arise from solving for the present discounted value of the dividends.

Suppose that firm i's operating cash flows are a constant fraction of output, y_t, and hence monetary policy will affect dividends through its effect on output. Moreover, suppose that monetary policy can affect dividends directly as well, for example by reducing the real value of nominal obligations as in Gomes and Schmid (2015) and Ozdagli and Weber (2017). A stylized way to incorporate these assumptions would be to write the dividends of firm i as

$$\begin{aligned} D_{i,t} &= a_i y_t + b_i M_t + \vartheta_i e^{\zeta_i w_{i,t}} \text{ with } a_i > 0, b_i > 0, \text{ and} \\ M_t &= e^{\chi m_t} \text{ with } \chi > 0, \end{aligned}$$

where $dw_{i,t}$ is a Brownian increment and $\vartheta_i e^{\zeta_i w_{i,t}}$ is the idiosyncratic (non-systematic) component of the dividends.

For simplicity and without loss of generality, we assume that a_i, b_i, and ϑ_i are constant. The value of the firm is given by the present discounted value of dividends

$$V_{i,t} = E_t \int_0^\infty \frac{\Lambda_{t+s}}{\Lambda_t} D_{i,t+s} ds = E_t \int_0^\infty \frac{\Lambda_{t+s}}{\Lambda_t} \left(a_i y_{t+s} + b_i M_{t+s} + \vartheta_i e^{\zeta_i w_{i,t}} \right) ds.$$

We assume all cash flows, such as dividends, nominal obligations, and other profits and losses generated outside the stock market, ends up with consumers, so that $c_t = y_t$ and $\Lambda_{t+s}/\Lambda_t = exp(-\rho s)(y_{t+s}/y_t)^{-\gamma}$. Output follows the process described in Appendix A.2.

After solving the associated Hamilton-Jacobi-Bellman equation, we get

$$V_{i,t} = \frac{a_i y_t}{r - \mu + \gamma \theta_y^2} + \frac{b_i M_t}{r - \frac{1}{2}\chi^2 - \gamma \chi \left(\theta_M - \eta_A \theta_A \right)} + \frac{\vartheta_i e^{\zeta_i w_{i,t}}}{r - \frac{1}{2}\zeta_i^2},$$

which will help us solve for the stock returns of the firm, dR_i. In particular,

$$dR_i = \frac{D_i dt + dV_i}{V_i}$$

where we dropped time indices for simplicity. We can calculate dV_i using Ito's Lemma to get

$$dR_i = (r + \phi_i)\, dt + \frac{V_{i,y} y}{V_i} \theta_y dw_y + \frac{V_{i,M} M}{V_i} \chi dm + \left(1 - \frac{V_{i,y} y}{V_i} - \frac{V_{i,M} M}{V_i}\right) \zeta_i dw_i$$

where V_y and V_M are partial derivatives with respect to y and M, and ϕ_i is the equity premium given by $E_t\left(-\frac{d\Lambda}{\Lambda} dR_i\right)$.

Using $\theta_y dw_y = \theta_A dw_A + \theta_M dm$ and the solution for V_i, we get

$$dR_i = (r + \phi_i)\, dt + \psi_{i,y} \theta_A dw_A + (\psi_{i,M} \chi + \psi_{i,y} \theta_M)\, dm + (1 - \psi_{i,y} - \psi_{i,M})\, \zeta_i dw_i,$$

where $\psi_{i,y} = a_i y / \left[\left(r - \mu + \gamma \theta_y^2\right) V_i\right]$ and $\psi_{i,M} = b_i M / \left[\left(r - \frac{1}{2}\chi^2 - \gamma \chi \left(\theta_M - \eta_A \theta_A\right)\right) V_i\right]$. This process has the same form as the process of R_i in Appendix A.2 where $\sigma_{A,i} = \psi_{i,y} \theta_A$, $\sigma_{M,i} = (\psi_{i,M} \chi + \psi_{i,y} \theta_M)$, and $\sigma_i = (1 - \psi_{i,y} - \psi_{i,M})\, \zeta_i$. As seen here, $\sigma_{A,i}$, $\sigma_{M,i}$, and σ_i can be time-varying, which does not pose any problems for the intuition in Appendix A.2.

It is also straightforward to show that the market return, R^*, follows the stochastic differential equation (23) in Section A.3 in this setting. In particular, suppose that we have a continuous distribution of firms, $f(a, b, \zeta, \vartheta, w)$, which captures the frequency of firms with $a_i = a$, $b_i = b$, $\zeta_i = \zeta, \vartheta_i = \vartheta$, and $w_{i,t} = w$. Therefore, to simplify notation, we can index firms by $z = (a, b, \zeta, \vartheta, w)$, abbreviate $f(a, b, \zeta, \vartheta, w)$ as $f(z)$, and define its domain as Z. We denote the individual stock values and returns of a firm that is characterized by a particular value of z at a moment when output is equal to y and state of monetary policy is equal to m as $V(z, y, m)$ and $dR(z, y, m)$.

The aggregate stock returns are then given by the value-weighted average of individual returns,

$$dR^*(y,m) = \int_Z \frac{V(z,y,m)\, dR(z,y,m)}{V^*(y,m)} dF(z),$$

where $dF(z) = f(z)\, dz$, and $V^*(y,m) = \int_Z V(z,y,m)\, dF(z)$ is the aggregate stock market value. To simplify the notation further, we drop (y,m) from the arguments since the distribution of z is independent of (y,m).

Using the formula for individual returns derived earlier, we get

$$\begin{aligned} dR^* &= \left(r + \int_Z \phi(z)\, V(z)\, dF(z)\right) dt + \int_Z \frac{V_y(z)\, y}{V^*} dF(z)\, \theta_y dw_y + \int_Z \frac{V_M(z)\, M}{V^*} dF(z)\, \chi dm \\ &\quad + \left[\int_Z \zeta(z) \left(1 - \frac{V_{i,y}(z)\, y}{V^*} - \frac{V_{i,M}(z)\, M}{V^*}\right) dw(z)\, dF(z)\right]. \end{aligned}$$

where $dw(z)$ is the Brownian idiosyncratic shock for firm with state z. Since these shocks are i.i.d. with mean zero and $dw(z)$ is independent of z, the last term on the right side of this equation is equal to zero. Therefore, the process to market return simplifies to

$$dR^* = (r + \phi^*)\, dt + \psi_y^* \theta_y dw_y + \psi_M^* \chi dm,$$

where

$$\begin{aligned} \phi^* &= \int_Z \phi(z)\, V(z)\, dF(z) = E\left(\frac{d\Lambda}{\Lambda} dR^*\right), \\ \psi_y^* &= \int_Z \frac{V_y(z)\, y}{V^*} dF(z), \\ \psi_M^* &= \int_Z \frac{V_M(z)\, M}{V^*} dF(z). \end{aligned}$$

Plugging $\theta_y dw_y = \theta_A dw_A + \theta_M dm$, we get

$$dR_i = (r + \phi^*)\, dt + \psi_y^* \theta_A dw_A + \left(\psi_M^* \chi + \psi_y^* \theta_M\right) dm.$$

This process has the same form as the process of R^* in equation (23) in Section A.3 where $\sigma_A^* = \psi_y^* \theta_A$ and $\sigma_M^* = \psi_M^* \chi + \psi_y^* \theta_M$. Moreover, we can show that the condition for the failure of CAPM, $\sigma_M^* - \eta_A \sigma_A^* = 0$, is consistent with the condition of negative monetary policy risk premium, $\theta_M - \theta_A \eta_A < 0$. In particular, we can rewrite this condition as

$$\sigma_M^* - \eta_A \sigma_A^* = \left(\psi_M^* \chi + \psi_y^* \theta_M\right) - \eta_A \psi_y^* \theta_A = 0$$

which implies

$$\psi_y^* \left[\theta_M - \eta_A \theta_A\right] = -\psi_M^* \chi < 0,$$

thereby satisfying the condition for negative monetary policy risk premium, $\theta_M - \theta_A \eta_A < 0$.[13]

Note that this example is one possible, but not the only, case that can lead to such a process for R^*. Moreover, the failure of CAPM is even easier to generate under more general conditions. For example, there may be factors that can affect how the output of the firm is divided between shareholders and other stakeholders, such as time varying labor share of production. This would imply that a_i and a are evolving stochastically over time. The true stochastic discount factor, Λ, would price the movements in a_i and a to the extent the factors underlying these movements are correlated with consumption. However, CAPM would try to price the movements in a_i even if the underlying factors are uncorrelated with consumption because R^* would be affected by the movements in a which would still be correlated with a_i. In sum, we present one stylized example of how CAPM can fail among many possibilities.

[13] To be more precise, since ψ^* are time-varying in this model the failure of CAPM holds on average, that is, $E(\sigma_M^* - \eta_A \sigma_A^*) = 0$. Similarly, monetary policy risk premium is negative on average.

II Alternative measurement of monetary policy exposure using direct estimation

The main challenge in studying the impact of monetary policy on the cross-section of expected stock returns arises from the difficulty in measuring firms' exposure to monetary policy. We address this challenge by creating a parsimonious monetary policy exposure index that captures the multidimensional nature of the cross-sectional variation in policy sensitivity.

A direct approach, where one regresses individual stock returns on monetary policy surprises without interaction with any firm characteristics, is not as fruitful because the majority of stocks have high return volatility or lack a long enough return history, leading to imprecise coefficient estimates. Moreover, a few outliers can significantly affect the estimates of the policy exposure of individual stocks based on this direct approach whereas the estimation procedure of our MPE index uses the full sample of returns of all stocks simultaneously, thereby significantly reducing the influence of individual outliers. Nevertheless, if we are content with these limitations we can create directly-estimated policy exposures and compare their ability with that of our MPE index.

The directly-estimated policy exposures are created using the regression $r_{it} = \alpha_i + \beta_i \text{MPS}_t + \varepsilon_{it}$, where MPS_t is the monetary policy surprise and r_{it} is the intraday return on stock i, both calculated using the first trade following 20 minutes after the announcement and the last trade before 10 minutes prior to the announcements. In order to reduce the effect of the outliers and improve the precision of estimates, we follow Bernanke and Kuttner (2005) and drop those observations for which Cook's D-statistic is greater than 0.1 and also discard zero returns and returns from trades that do not happen within 90 minutes of FOMC announcements. We calculate these directly-estimated policy betas using the historically available information in an expanding window as we do with the expanding-window portfolios based on the MPE index in Table 5.

Table II.1 reports average excess returns and alphas from factor models and a spanning test controlling for the expanding-window MPE strategy from Table 5. We report the results for the five portfolios constructed from a sort on directly-estimated policy betas, as well as a portfolio long stocks with low directly-estimated policy betas and short stocks with high directly-estimated policy betas. The sample begins in December, 1996, using 24 FOMC meetings between February 1994 and December 1996 for the first set of policy betas.

The long/short portfolio based on directly-estimated policy betas generates a sizable spread of 55 basis points per month in returns, which is (at least marginally) statistically significant with a t-statistic of 1.73. The alphas from controlling for CAPM, three-factor, and four-factor models are also sizable and at least marginally significant. The lowest alpha (29 bp) and test-statistic (1.27) arise when controlling for the Fama and French (2015) five-factor model, part of which can be attributed to smaller sample size. Nevertheless, controlling *only* for the expanding-window MPE strategy from Table 5, we obtain a marginally lower alpha (27 bp) with much lower statistical significance ($t = 0.88$).[14] The results are consistent with the notion that the directly-estimated policy betas are simply a noisier version of our monetary policy exposure index and highlights the benefit of using the MPE index. Moreover, unlike directly-estimated betas, our index allows us to study the behavior of the returns that goes beyond the period which we have used to estimate our index.

[14]The positive alphas of portfolios (L) through (H) with respect to the MPE strategy reflect the fact we are not including the market factor on the right-hand-side. The reason for not including the market factor is that we are interested in the performance of the long/short directly-estimated-policy-beta portfolio in a spanning test controlling for the long/short MPE portfolio.

Table II.1

Directly-estimated-policy-beta Portfolio Performance

This table reports average excess returns and alphas from factor models and a spanning test controlling for the MPE strategy from Table 5. In each month, firms are sorted by their directly-estimated monetary policy betas into quintiles based on NYSE breakpoints. These directly-estimated betas are generated from the regression $r_{it} = \alpha_i + \beta_i \text{MPS}_t + \varepsilon_{it}$, where MPS_t is the monetary policy surprise and r_{it} is the intraday return on stock i, both calculated using the first trade following 20 minutes after the announcement and the last trade before 10 minutes prior to the announcements. For each of the five portfolios, and for a portfolio long stocks with low directly-estimated betas and short stocks with high directly-estimated betas, we report average value-weighted returns in excess of the risk-free rate and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, the Fama and French (2015) five-factor model, and a spanning test controlling for the expanding window MPE strategy performance from Table 5. T-statistics are in brackets. Sample period is 12/1996 to 07/2008.

	(L)	(2)	(3)	(4)	(H)	(L-H)
r^e	0.55	0.55	0.41	0.49	0.00	0.55
	[1.59]	[1.86]	[1.07]	[1.15]	[0.00]	[1.73]
α^{CAPM}	0.27	0.32	0.08	0.12	-0.46	0.73
	[1.70]	[2.05]	[0.65]	[0.94]	[-2.91]	[2.90]
α^{FF3}	0.17	0.21	0.13	0.13	-0.42	0.59
	[1.06]	[1.65]	[1.10]	[1.13]	[-2.90]	[2.40]
$\alpha^{\text{FF3+UMD}}$	0.05	0.14	0.13	0.22	-0.36	0.41
	[0.30]	[1.09]	[1.04]	[1.91]	[-2.49]	[1.72]
α^{FF5}	0.03	0.03	0.09	0.18	-0.26	0.29
	[0.18]	[0.21]	[0.77]	[1.46]	[-1.97]	[1.27]
α_{MPE}	1.05	0.90	0.99	1.03	0.78	0.27
	[3.03]	[2.97]	[2.65]	[2.44]	[1.53]	[0.88]

III Robustness to strategy construction

This section shows that the cross-sectional return predictability of monetary policy exposure (MPE) in the time-series portfolio tests is not sensitive to the choice of portfolio construction. Table III.1 reports excess returns and alphas with respect to factor models on portfolio sorts on MPE, analogous to the ones in Panel A of Table 3, with different portfolio construction strategies. Panel A of Table III.1 reports results for value-weighted portfolios, constructed using a quintile sort of all stocks to determine the breakpoints instead of breakpoints based on only NYSE stocks. We can observe that the long/short portfolio achieves average monthly returns of almost one percent, with a highly significant t-statistic of 5.34. Even after controlling for the Fama and French (2015) five factors, we are left with an alpha of 0.54% per month with a t-statistic of 4.18. The fact that the results are stronger in Table III.1 than in Table 3 is not surprising. Using NYSE breakpoints ensures that there are equal number of NYSE stocks in each portfolio. Since NYSE stocks tend to be bigger, using all stocks for breakpoints can result in relatively fewer large-capitalization stocks in the extreme portfolios, which tends to make the results stronger, even when using value-weighting.

Similarly, Panel B contains results from a quintile sort using NYSE breakpoints, but with equal-weighted portfolios. We can observe that the average returns to the long/short portfolio are even stronger, at 1.06% per month, with an even bigger t-statistic of 8.39. As Novy-Marx and Velikov (2016) note, however, equal-weighting tends to produce stronger results due to the influence of micro- and small-capitalization stocks, which tend to be less liquid and more expensive to trade, which is why throughout this study we employ value-weighting.

Finally, Panel C shows that a more extreme sort also results in stronger performance. The long/short portfolio on a decile strategy using value-weighted portfolio returns and NYSE breakpoints earns just under one percent per month on average, with a t-statistic of 5.28. Even after controlling for the Fama and French (2015) five factors, we are left with an alpha of 0.48% per month with an associated t-statistic of 3.96.

Table III.1

Robustness to strategy construction

This table reports average excess returns and alphas with respect to factor models on portfolio sorts on MPE, similar to the ones in Table 3, Panel A. In each month, firms are sorted by their monetary policy exposure (MPE). MPE is estimated using equation (4) from the text. For each portfolio, and for a portfolio long stocks with low MPE and short stocks with high MPE, average returns in excess of the risk-free rate and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2015) five-factor model are reported. Panel A reports results using value-weighted portfolios, constructed from a quintile sort with all stock breakpoints. Panel B reports results using equal-weighted portfolios, constructed from a quintile sort with NYSE breakpoints. Panel C reports results using value-weighted portfolios, constructed from a decile sort with NYSE breakpoints. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Panel A: Quintile sort, value-weighted, all breaks						
	(L)	(2)	(3)	(4)	(H)	(L-H)
r^e	1.54	1.18	1.02	0.77	0.58	0.96
	[5.63]	[4.63]	[4.11]	[3.49]	[2.82]	[5.34]
α^{CAPM}	0.83	0.47	0.29	0.10	-0.06	0.89
	[5.14]	[3.68]	[2.86]	[1.38]	[-1.23]	[4.91]
α^{FF3}	0.55	0.30	0.16	0.03	0.03	0.53
	[4.61]	[3.32]	[1.87]	[0.37]	[0.64]	[4.09]
$\alpha^{\text{FF3+UMD}}$	0.81	0.43	0.28	0.10	0.02	0.79
	[7.47]	[5.03]	[3.26]	[1.43]	[0.47]	[6.71]
α^{FF5}	0.54	0.28	0.13	-0.03	-0.01	0.54
	[4.42]	[3.08]	[1.42]	[-0.45]	[-0.15]	[4.18]
Panel B: Quintile sort, equal-weighted, NYSE breaks						
r^e	1.55	0.92	0.80	0.73	0.48	1.06
	[5.51]	[3.36]	[2.96]	[2.74]	[1.73]	[8.39]
α^{CAPM}	0.84	0.15	0.02	-0.05	-0.32	1.16
	[4.78]	[1.14]	[0.18]	[-0.49]	[-2.59]	[9.30]
α^{FF3}	0.58	-0.04	-0.15	-0.18	-0.38	0.96
	[4.99]	[-0.58]	[-2.17]	[-2.57]	[-4.52]	[8.60]
$\alpha^{\text{FF3+UMD}}$	0.81	0.12	-0.01	-0.06	-0.26	1.07
	[7.71]	[1.85]	[-0.08]	[-0.93]	[-3.21]	[9.69]
α^{FF5}	0.66	0.03	-0.12	-0.11	-0.18	0.84
	[5.60]	[0.34]	[-1.63]	[-1.53]	[-2.30]	[7.54]

Table III.1 (Continued): Robustness to strategy construction

Panel C: Decile sort, value-weighted, NYSE breaks											
	(L)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(H)	(L-H)
r^e	1.44	1.20	1.12	0.98	0.79	0.93	0.78	0.67	0.63	0.51	0.93
	[5.48]	[4.62]	[4.49]	[3.91]	[3.29]	[4.09]	[3.57]	[3.26]	[3.08]	[2.39]	[5.28]
α^{CAPM}	0.74	0.48	0.40	0.26	0.08	0.26	0.13	0.05	0.01	-0.14	0.88
	[5.04]	[3.64]	[3.61]	[2.30]	[0.86]	[2.87]	[1.56]	[0.73]	[0.14]	[-1.98]	[4.94]
α^{FF3}	0.49	0.28	0.27	0.12	-0.02	0.19	0.08	0.04	0.07	-0.02	0.50
	[4.85]	[3.04]	[3.00]	[1.23]	[-0.23]	[2.12]	[0.98]	[0.48]	[1.10]	[-0.24]	[4.18]
$\alpha^{\text{FF3+UMD}}$	0.68	0.42	0.36	0.26	0.06	0.26	0.14	0.03	0.06	-0.03	0.70
	[7.30]	[4.82]	[4.12]	[2.66]	[0.72]	[2.85]	[1.60]	[0.46]	[0.94]	[-0.42]	[6.19]
α^{FF5}	0.45	0.29	0.22	0.10	-0.02	0.07	0.02	-0.06	-0.04	-0.03	0.48
	[4.49]	[3.11]	[2.50]	[0.95]	[-0.18]	[0.74]	[0.23]	[-0.75]	[-0.59]	[-0.42]	[3.96]

IV Robustness to underlying characteristics

In this section we examine the cross-sectional return predictability of monetary policy exposure controlling for the characteristics used to construct the index. Table IV.1 reports results from conditional double sorts on the characteristics and MPE. In each month, firms are first sorted into quintiles based on one of the five characteristics. Then, within each quintile, stocks are further sorted into quintiles based on their MPE, which leads to 5x5 portfolios as in Table 8. As a final step, the firms in the resulting 5x5 portfolios are collapsed into five MPE-based portfolios by combining the firms in each characteristic decile for a given MPE quintile. The table reports average value-weighted excess returns to the resulting five MPE-based portfolios conditioned on each characteristic, as well as to a portfolio long stocks with low MPE and short stocks with high MPE. We can observe that MPE preserves it predictive ability controlling for the underlying characteristics. The lowest average monthly return on the long/short portfolios in the double sorts is achieved when conditioning on the operating profitability, but even in that case it amounts to 47 basis points, an estimate over two standard errors above zero.

Similarly, Table IV.2 documents results from spanning tests, in which the returns to the long/short portfolio from Table 3 are regressed on a constant term and the returns to strategies constructed by quintile sorts on the underlying characteristics used to construct the monetary policy exposure measure. The results imply that the strategy based on monetary policy exposure is outside of the span of the strategies based on the underlying characteristics. For example, specification (5) shows that the monetary policy exposure strategy has a significant alpha of 49 basis points per month (t-statistic of 3.47) with respect to the strategy based on operating profitability.

Finally, Table IV.3 reports results from estimating Fama-MacBeth regressions of firms' returns on monetary policy exposure and the underlying characteristics. Specifications (1) - (5) each control for one of the characteristics at a time. We can observe that MPE has significant predictive power beyond that in the characteristics used to construct it. The lowest t-statistic (in absolute value) on MPE is in specification (5), which controls for Operating Profitability. Even in that specification, however, the estimated coefficient on MPE is close to five standard errors below zero.

Table IV.1

Robustness to underlying characteristics: Double sorts

This table reports average returns for double sorted MPE portfolios. In each month, firms are sorted into quintiles based on one of the characteristics underlying the MPE index. Then, within each quintile, firms are further sorted in quintiles based on MPE. Firms are grouped into five MPE-based portfolios by combining the firms across the characteristic quintiles. The table reports value-weighted average excess returns for the five MPE portfolios and for a portfolio that is long stocks in the low MPE portfolio and short stocks in the high MPE portfolio. MPE is estimated using equation (4) from the text. T-statistics are reported in brackets. The sample period is 01/1975 to 12/2015.

		MPE Quintiles					
		(L)	(2)	(3)	(4)	(H)	(L-H)
Conditioning Variables	Cash	1.35	1.01	0.87	0.76	0.57	0.78
		[5.44]	[4.18]	[3.68]	[3.56]	[2.79]	[4.85]
	CF Duration	1.48	1.09	0.93	0.79	0.57	0.92
		[5.15]	[4.13]	[3.71]	[3.40]	[2.84]	[5.01]
	Whited-Wu	1.19	0.93	0.84	0.61	0.49	0.70
		[4.93]	[4.19]	[4.02]	[2.99]	[2.24]	[4.57]
	CF Volatility	1.52	1.18	1.10	0.85	0.56	0.95
		[5.36]	[4.46]	[4.39]	[3.67]	[2.77]	[5.04]
	Op. Profit.	1.06	0.89	0.87	0.66	0.59	0.47
		[3.60]	[3.43]	[3.42]	[2.95]	[2.94]	[2.42]

Table IV.2

Robustness to underlying characteristics: Spanning Tests

The table documents results from time-series regressions of the returns to the strategy from table 3 on returns to strategies constructed from the variables used to derive the monetary policy exposure (MPE). MPE is estimated using equation (4) from the text. All strategies are constructed on the same sample from a quintile sort using NYSE breakpoints. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Regressions of the form $R_{t,MPE} = \alpha + \beta_X R_{X,t} + \varepsilon_t$					
Coefficient	(1)	(2)	(3)	(4)	(5)
Const	0.48	0.68	0.60	0.77	0.49
	[3.47]	[4.60]	[4.72]	[5.02]	[3.47]
β_{Cash}	41.13				
	[11.81]				
$\beta_{\text{CF Duration}}$		-32.17			
		[-7.94]			
$\beta_{\text{Whited Wu}}$			42.67		
			[15.45]		
$\beta_{\text{CF Volatility}}$				18.47	
				[4.20]	
$\beta_{\text{Operating Profitability}}$					47.98
					[11.09]

Table IV.3

Robustness to underlying characteristics: Fama-MacBeth regressions

The table documents results from Fama-MacBeth regressions of the form $r_{tj} = \beta' \mathbf{x}_{t-1,j} + \varepsilon_{tj}$. The characteristics $\mathbf{x}_{t-1,j}$ include monetary policy exposure and combinations of characteristics used to construct the monetary policy exposure index. MPE is estimated using equation (4) from the text. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

	Regressions of the form $r_{tj} = \beta' \mathbf{x}_{t-1,j} + \varepsilon_{tj}$				
Coefficient	(1)	(2)	(3)	(4)	(5)
MPE	-0.51	-0.69	-0.83	-0.67	-0.48
	[-7.71]	[-8.15]	[-9.51]	[-8.23]	[-4.94]
Cash	1.03				
	[4.47]				
CF Duration		0.12			
		[0.46]			
Whited Wu			-0.49		
			[-1.40]		
CF Volatility				0.50	
				[0.40]	
Operating Profitability					3.66
					[3.09]

V Robustness to other anomalies

This section shows that the return predictability we document is not a different anomaly in disguise. To this end, Table V.1 reports average excess returns for conditional MPE strategies, constructed from double-sorts on each of the twenty-three anomaly signals from Novy-Marx and Velikov (2016) and MPE. In each month, firms are sorted into quintiles based on one of the twenty-three anomaly signals. Then, within each quintile, stocks are further sorted into quintiles based on their MPE, which leads to 5x5 portfolios as in Table 8. As a final step, the firms in the resulting 5x5 portfolios are collapsed into five MPE-based portfolios by combining the firms in each characteristic decile for a given MPE quintile. The table reports average value-weighted excess returns to the resulting five MPE-based portfolios conditioned on each signal, as well as to a portfolio long stocks with low MPE and short stocks with high MPE. We can observe that the MPE strategies earn significantly positive returns on average, conditioning on any of the signals. The lowest average returns are earned by the MPE strategy constructed conditioning on the combined value and gross profitability signals (ValProf). However, even in that case, the MPE strategy earns an average return of 36 basis points with a t-statistic of 2.22.

Table V.2 reports average excess returns and spanning tests between the strategy examined in Table 3 and the twenty-three anomalies from Novy-Marx and Velikov (2016). The spanning tests also confirm the findings from Table V.1 and show that the MPE strategy has a positive and highly statistically significant information ratio relative to all of the twenty-three anomalies separately. Similar to the double sorts, the lowest alpha is achieved after controlling for the ValProf anomaly, but even in that case, as Panel B reports, it earns about 0.34% per month with a t-statistic of 2.56.

Finally, Table V.3 reports results from estimating Fama-MacBeth regressions of firms' returns on monetary policy exposure ($\times -1$) and each of the anomaly characteristics individually. Again, we can observe that MPE has strong cross-sectional return predictive power that goes beyond the one contained in each of the twenty-three anomaly signals.

Table V.1

Robustness to other anomalies: Double sorts

The table reports average excess returns for conditional monetary policy exposure (MPE) strategies, constructed from double-sorts on each of the twenty-three anomaly signals from Novy-Marx and Velikov (2016) and MPE. In each month, all firms in the CRSP/COMPUSTAT merged database are sorted into quintiles based on one of the twenty-three signals. Then, within each quintile, stocks are sorted into quintiles based on their MPE. Firms are grouped into five MPE-based portfolios by combining the firms across the characteristic quintiles. The table reports value-weighted average excess returns for the five MPE portfolios and for a portfolio that is long stocks in the low MPE portfolio and short stocks in the high MPE portfolio. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Anomaly	Size	Gross Profitability	Value	ValProf	Accruals	Asset Growth	Investment	Piotroski F-score	Net Issuance (M)	ROE	Failure Probability	ValMomProf	ValMom	Idiosyncratic Volatility	Momentum	PEAD (SUE)	PEAD (CAR3)	Industry Momentum	Industry Relative Reversals	High-frequency Combo	Short-run Reversals	Seasonality	IRR (LowVol)
(L)	0.97	1.07	1.07	0.93	1.30	1.17	1.14	1.33	1.39	1.51	1.47	1.30	1.47	1.32	1.53	1.50	1.45	1.51	1.46	1.54	1.40	1.55	1.05
	[4.13]	[4.18]	[3.98]	[3.41]	[5.16]	[4.45]	[4.43]	[5.14]	[4.98]	[5.85]	[6.10]	[4.49]	[5.40]	[5.87]	[6.01]	[5.69]	[5.44]	[5.68]	[5.57]	[5.68]	[5.34]	[5.95]	[4.95]
(2)	0.91	0.98	0.86	0.74	0.99	0.93	0.95	1.01	1.16	1.24	1.17	1.01	1.18	1.09	1.23	1.16	1.20	1.17	1.16	1.21	1.16	1.19	1.02
	[4.02]	[3.77]	[3.38]	[2.82]	[4.01]	[3.69]	[3.80]	[4.04]	[4.39]	[4.96]	[4.84]	[3.72]	[4.66]	[4.82]	[4.91]	[4.66]	[4.75]	[4.70]	[4.61]	[4.78]	[4.66]	[4.85]	[4.62]
(3)	0.75	0.81	0.77	0.70	0.90	0.80	0.80	0.86	0.92	1.00	0.90	0.92	1.04	0.86	0.89	1.01	0.94	0.96	0.92	0.94	0.92	0.95	0.84
	[3.55]	[3.30]	[3.21]	[2.89]	[3.69]	[3.15]	[3.27]	[3.43]	[3.63]	[4.19]	[3.81]	[3.66]	[4.18]	[3.91]	[3.67]	[4.12]	[3.89]	[3.96]	[3.86]	[3.87]	[3.79]	[3.95]	[4.12]
(4)	0.58	0.67	0.72	0.63	0.76	0.70	0.72	0.71	0.78	0.81	0.74	0.74	0.80	0.75	0.84	0.78	0.83	0.73	0.79	0.78	0.77	0.81	0.70
	[2.87]	[3.01]	[3.35]	[2.95]	[3.48]	[3.14]	[3.22]	[3.14]	[3.50]	[3.74]	[3.49]	[3.32]	[3.57]	[3.68]	[3.83]	[3.57]	[3.80]	[3.40]	[3.68]	[3.59]	[3.55]	[3.79]	[3.59]
(H)	0.46	0.57	0.52	0.58	0.54	0.55	0.55	0.55	0.58	0.55	0.56	0.58	0.56	0.55	0.57	0.58	0.56	0.57	0.57	0.56	0.57	0.57	0.65
	[2.14]	[2.79]	[2.52]	[2.83]	[2.67]	[2.70]	[2.73]	[2.73]	[2.84]	[2.70]	[2.73]	[2.86]	[2.77]	[2.61]	[2.78]	[2.87]	[2.75]	[2.81]	[2.78]	[2.73]	[2.80]	[2.81]	[3.42]
(L-H)	0.51	0.50	0.56	0.36	0.75	0.62	0.58	0.78	0.81	0.95	0.91	0.72	0.90	0.77	0.96	0.92	0.89	0.94	0.89	0.98	0.83	0.98	0.40
	[4.01]	[3.13]	[3.49]	[2.22]	[4.78]	[3.82]	[3.63]	[4.70]	[4.63]	[5.87]	[6.18]	[3.70]	[5.10]	[5.41]	[5.95]	[5.34]	[5.08]	[5.56]	[5.22]	[5.62]	[4.97]	[5.74]	[2.71]

Table V.2

Robustness to other anomalies: Spanning tests

The table reports average excess returns and spanning tests for the strategy examined in Table 3 and strategies that use one the twenty-three signals from Novy-Marx and Velikov (2016). The strategies consist of long/short portfolios, constructed using quintile sorts with NYSE breakpoints. Panel A reports value-weighted average excess returns on the twenty-three strategies, Panel B reports spanning tests of the form $R_{t,i} = \alpha + \beta R_{t,MPE} + \varepsilon_t$, and Panel C reports spanning tests of the form $R_{t,MPE} = \alpha + \beta R_{t,i} + \varepsilon_t$, where $R_{t,i}$ is one of the twenty-three anomaly strategies, and $R_{t,MPE}$ is the return on the strategy from Table 3. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Anomaly	Size	Gross Profitability	Value	ValProf	Accruals	Asset Growth	Investment	Piotroski F-score	Net Issuance (M)	ROE	Failure Probability	ValMomProf	ValMom	Idiosyncratic Volatility	Momentum	PEAD (SUE)	PEAD (CAR3)	Industry Momentum	Industry Relative Reversals	High-frequency Combo	Short-run Reversals	Seasonality	IRR (LowVol)
Panel A: Excess returns on 23 anomalies from Novy-Marx and Velikov (2016)																							
	0.26	0.27	0.35	0.75	0.16	0.27	0.30	0.25	0.36	0.46	0.33	0.96	0.60	0.23	0.74	0.36	0.49	0.61	0.75	0.94	0.35	0.56	1.04
	[1.35]	[2.18]	[2.33]	[5.03]	[1.42]	[1.95]	[2.66]	[1.98]	[2.73]	[2.75]	[1.32]	[4.98]	[2.94]	[0.83]	[2.93]	[3.48]	[4.77]	[3.10]	[5.05]	[6.63]	[1.72]	[4.07]	[9.09]
Panel B: Spanning tests of the form $R_{t,MPE} = \alpha + \beta R_{t,i} + \varepsilon_t$																							
α	0.63	0.83	0.63	0.34	0.79	0.70	0.73	0.86	0.86	0.98	0.89	0.74	0.90	0.83	0.90	0.81	0.90	0.82	0.60	0.77	0.72	0.87	0.51
	[5.83]	[5.37]	[4.39]	[2.56]	[5.11]	[4.59]	[4.69]	[5.81]	[5.65]	[7.04]	[6.43]	[4.63]	[6.01]	[5.95]	[6.02]	[5.16]	[5.72]	[5.25]	[3.86]	[4.74]	[4.68]	[5.62]	[3.07]
β	60.21	-22.19	41.05	59.11	-15.73	22.28	9.86	-38.67	-27.02	-43.96	-30.28	2.57	-22.51	-25.32	-18.41	-12.87	-26.98	-9.14	22.88	-0.72	15.64	-20.92	25.20
	[23.09]	[-3.96]	[9.48]	[14.66]	[-2.59]	[4.56]	[1.61]	[-7.39]	[-5.14]	[-11.50]	[-11.79]	[0.70]	[-6.76]	[-10.96]	[-6.84]	[-1.85]	[-3.95]	[-2.57]	[4.75]	[-0.14]	[4.56]	[-4.07]	[3.93]
Panel C: Spanning tests of the form $R_{t,i} = \alpha + \beta R_{t,MPE} + \varepsilon_t$																							
	-0.44	0.39	0.03	0.32	0.24	0.13	0.26	0.45	0.52	0.87	0.96	0.93	0.91	0.86	1.13	0.41	0.59	0.73	0.56	0.93	0.11	0.65	0.91
	[-3.31]	[3.13]	[0.25]	[2.59]	[2.08]	[0.93]	[2.25]	[3.63]	[3.98]	[5.83]	[4.40]	[4.69]	[4.61]	[3.44]	[4.61]	[4.04]	[5.74]	[3.64]	[3.91]	[6.43]	[0.55]	[4.79]	[8.36]
	86.61	-14.01	37.84	51.66	-8.61	18.28	5.36	-25.97	-18.96	-48.40	-73.05	3.95	-37.92	-77.91	-47.49	-5.38	-11.45	-14.61	19.28	-0.59	26.11	-15.65	12.13
	[23.09]	[-3.96]	[9.48]	[14.66]	[-2.59]	[4.56]	[1.61]	[-7.39]	[-5.14]	[-11.50]	[-11.79]	[0.70]	[-6.76]	[-10.96]	[-6.84]	[-1.85]	[-3.95]	[-2.57]	[4.75]	[-0.14]	[4.56]	[-4.07]	[3.93]

Table V.3

Robustness to other anomalies: Fama-MacBeth regressions

The table documents results from Fama-MacBeth regressions of the form $r_{tj} = \beta' \mathbf{x}_{t-1,j} + \varepsilon_{tj}$. The characteristics $x_{t-1,j}$ include monetary policy exposure and anomaly signal characteristics from Novy-Marx and Velikov (2016). Monetary policy exposure is estimated using the coefficients on the interaction terms from Table 1. Panel A reports reports estimates from regressing returns on each of the twenty-three characteristics alone, while the regressions in Panel B also include MPE. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Anomaly	Size	Gross Profitability	Value	ValProf	Accruals	Asset Growth	Investment	Piotroski F-score	Net Issuance (M)	ROE	Failure Probability	ValMomProf	ValMom	Idiosyncratic Volatility	Momentum	PEAD (SUE)	PEAD (CAR3)	Industry Momentum	Industry Relative Reversals	High-frequency Combo	Short-run Reversals	Seasonality	IRR (LowVol)
Panel A: Fama-MacBeth Regressions of the form $r_{tj} = a + b_X X_{t-1,j} + \varepsilon_{tj}$																							
b_X	0.00	0.52	0.24	0.00	1.54	0.87	1.53	0.07	1.45	3.31	0.30	0.00	0.00	10.52	0.66	0.24	5.69	1.45	2.64	1.87	6.33	1.19	2.28
	[2.73]	[4.36]	[6.24]	[7.26]	[4.91]	[7.97]	[9.60]	[2.17]	[4.42]	[3.81]	[3.79]	[10.50]	[6.96]	[2.14]	[2.93]	[14.66]	[18.51]	[10.42]	[15.35]	[22.70]	[14.41]	[7.19]	[16.14]
Panel B: Fama-MacBeth Regressions of the form $r_{tj} = a + b_X \mathbf{X}_{t-1,j} + b_{\text{MPE}}(-\text{MPE}_{t-1,j}) + \varepsilon_{tj}$																							
b_{MPE}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
	[10.91]	[8.84]	[9.52]	[6.67]	[9.84]	[9.40]	[9.50]	[9.58]	[9.03]	[9.92]	[11.16]	[6.15]	[9.06]	[11.44]	[11.25]	[9.97]	[9.63]	[9.72]	[9.80]	[9.82]	[9.89]	[9.38]	[3.00]
b_X	0.00	-0.04	-0.01	0.00	1.30	0.66	1.04	0.04	1.23	2.87	0.30	0.00	0.00	14.62	0.57	0.25	5.75	1.22	2.16	1.51	4.41	0.84	1.93
	[1.12]	[-0.25]	[-0.14]	[1.34]	[4.03]	[5.43]	[5.01]	[1.28]	[3.21]	[4.51]	[3.92]	[3.61]	[3.07]	[2.61]	[3.02]	[15.34]	[17.06]	[6.38]	[9.67]	[15.79]	[9.14]	[6.48]	[13.16]

VI Robustness to exclusion of fixed effects

This section evaluates the robustness of our main results to the exclusion of fixed effects in the estimation in Table 1. Table VI.1 shows results for estimations of Equation 2, where fixed effects are not included as indicated in the bottom half of Panel A. Panel B reports the results for the average returns to the MPE-sorted portfolios, where the MPEs are calculated using the corresponding coefficients in Panel A. For comparison, the last column in the table reports the original coefficients on the interactions with the monetary policy surprise from Table 1 in Panel A and the average returns to the strategy from Table 3 in Panel B.

Discarding firm, industry, or rating fixed effects alone does not change the coefficients very significantly (columns 1–3) but discarding meeting fixed effects has a significant effect on the precision and value of coefficient estimates (column 4). Discarding meeting fixed effects also creates the largest drop in adjusted R^2 signifying the importance of its inclusion to get more precise coefficient estimates. Wald and likelihood ratio tests not reported in the table ($p < 0.01$) further confirm that meeting fixed effects are important. Not surprisingly, the R^2 drops even further when we drop all fixed effects (column 5). Nevertheless, in all specifications the low-minus-high MPE portfolio generates significant returns, ranging from 43 to 76 basis points per month.

Table VI.1

Robustness to fixed effects

This table evaluates the robustness of the MPE index to the inclusion of fixed effects in its estimation. Panel A reports estimates from panel OLS regressions following Table 1. Panel B reports the average returns to portfolios formed on MPE indices constructed using the corresponding coefficients in Panel A.

Panel A: Coefficients on interactions with MPS						
	(1)	(2)	(3)	(4)	(5)	(6)
MPS x Whited-Wu	-1.65	-1.34	-1.35	0.75	0.69	-1.60
	[-2.60]	[2.07]	[-2.20]	[0.92]	[1.05]	[-2.47]
MPS x Cash	-0.80	-0.11	-0.63	-0.98	0.18	-0.87
	[-1.94]	[-0.24]	[-1.59]	[-0.76]	[0.15]	[-2.12]
MPS x CF Duration	0.67	0.73	0.66	0.12	0.41	0.63
	[2.60]	[2.15]	[2.69]	[0.30]	[0.97]	[2.56]
MPS x CF Volatility	4.47	3.03	4.58	-0.92	-1.35	4.36
	[2.70]	[1.81]	[2.64]	[-0.37]	[-0.49]	[2.58]
MPS x Operating Profitability	-5.78	-3.11	-5.37	-17.27	-11.60	-5.74
	[-2.01]	[-1.53]	[-1.91]	[-3.02]	[-2.60]	[-2.02]
Firm FE	No	Yes	Yes	Yes	No	Yes
Meeting FE	Yes	Yes	Yes	No	No	Yes
Industry FE	Yes	No	Yes	Yes	No	Yes
Industry FE $\times$ MPS	Yes	No	Yes	Yes	No	Yes
Rating FE	Yes	Yes	No	Yes	No	Yes
Rating FE $\times$ MPS	Yes	Yes	No	Yes	No	Yes
n	229,394	229,103	229,355	229,091	229,677	229,061
$\bar{R}^2(\%)$	14.83	15.79	15.97	4.70	2.52	15.99
Panel B: Average returns to MPE strategy						
	(1)	(2)	(3)	(4)	(5)	(6)
(L)	1.28	1.25	1.27	1.05	0.96	1.30
	[5.02]	[4.96]	[5.07]	[4.70]	[4.71]	[5.08]
(2)	1.03	0.97	1.04	0.93	0.85	1.03
	[4.21]	[4.00]	[4.33]	[4.54]	[4.21]	[4.22]
(3)	0.88	0.90	0.87	0.75	0.71	0.87
	[3.87]	[4.09]	[3.93]	[3.74]	[3.67]	[3.84]
(4)	0.70	0.65	0.65	0.59	0.55	0.69
	[3.39]	[3.13]	[3.20]	[2.90]	[2.56]	[3.37]
(H)	0.53	0.58	0.56	0.43	0.53	0.53
	[2.57]	[2.78]	[2.66]	[1.74]	[1.99]	[2.58]
(L-H)	0.74	0.67	0.71	0.61	0.43	0.76
	[4.82]	[4.30]	[4.63]	[4.02]	[2.62]	[4.91]

VII Effect of different levels of economic activity

This section evaluates how our main results are affected when we use samples reflecting different levels of economic activity. In particular, there may be reasons that lead to different degrees of strength of the stabilizer channel depending on the level of economic activity. For example, when there is a high level of economic activity, investors may have lower risk aversion or the monetary policy may be less sensitive to economic shocks. Under these assumptions, when there is a high level of economic activity, the hedge provided by the monetary policy may be less valuable to investors and the stabilizer channel may be weaker.[15]

We use output gap estimates from Congressional Budget Office (CBO) and define high and low levels of economic activity as positive and negative output gap periods, as indicated in Panel A of Table VII.1. The first column of Panel B reproduces our original MPE-index estimation results using the FOMC dates in the full 1994–2008 sample. When we compare these estimates with those produced using only the positive output gap periods in column 2 and using only the negative output gap periods in column 3, we see that the estimates using the negative output gap periods are much closer to the full-sample results than the estimates using the positive output gap periods. Accordingly, we find that the average return generated by our long/short (low-minus-high MPE) portfolio over the whole 1975–2015 period is 80 basis points per month ($t = 5.05$) when using the MPE index generated from negative output gap periods whereas the same number is 58 basis points ($t = 4.26$) when using the MPE index generated from positive output gap periods. Nevertheless, in order to study the strength of the stabilizer channel in different periods, we need to match the type of subperiod for the portfolio return sample with the type of subperiod for the MPE-index estimation sample, as we do in Panel C.

Column 2 in Panel C presents the average returns in high activity periods during 1975–2015

[15] In our model in Appendix A.2, the stabilizer channel is independent of the *level* of economic activity because risk prices and exposures are constant. Within the context of our model, the additional assumptions about investors and the sensitivity of policy to economic shocks would be analogous to having a time-varying coefficient of relative risk aversion, e.g., $\gamma = \gamma(y_t)$ with $\gamma'(y_t) < 0$, or time varying sensitivity of monetary policy to economic shocks, e.g., $\eta_A = \eta_A(y_t)$ with $\eta'_A(y_t) < 0$. Alternatively, we can extend the model to have two macroeconomic regimes, which would make the solution of the model more complicated without providing additional intuition.

when we use the MPE index generated with the FOMC dates in the high activity periods in our estimation sample (1994–2008) from column 2 in Panel B. Column 3 repeats the same exercise for low activity periods. If the stabilizer channel is weaker during periods of high economic activity we should see that the average returns of the long/short portfolio should be lower in those periods. Indeed, this is what we observe when we compare columns 2 and 3 in Panel C with the difference being 47 ($= 79 - 32$) basis points. Moreover, the returns to the strategy in the high economic activity periods seem to be much less significant statistically as well.

One potential concern is that our results regarding the strength of the stabilizer channel is driven by the imprecise estimates of the MPE index in the positive-output-gap periods because there are relatively small number of FOMC meetings in the positive-output-gap periods in Panel B (28 vs 88). In order to address this concern, instead of choosing zero as the output gap cutoff, we choose the output gap cutoff as -0.97 in order to divide the MPE-estimation-sample into two groups with the same number of FOMC meetings (58 from third last row in Panel B) and repeat our exercises. The last two columns of Panel C show that the difference in the returns becomes even more stark, going up from 47 basis points to 83 ($= 98 - 15$) basis points.[16] Overall these results are broadly consistent with the notion that the stabilizer channel may be weaker during periods of high economic activity.

[16]We have tried alternatives, such as comparing top and bottom terciles of output gap or using unemployment gap instead – the results are qualitatively similar and available upon request.

Table VII.1

Effect of different levels of economic activity

This table evaluates how our main results are affected when we use samples reflecting different levels of economic activity. The regimes based on output gap (OGAP) from Haver Analytics are indicated in Panel A. Panel B reports estimates from panel regressions following Table 1. Panel C reports the average returns to portfolios formed on MPE indices constructed using the corresponding coefficients in Panel B for different regimes.

Panel A: Level of Economic Activity					
	(1)	(2)	(3)	(4)	(5)
	ALL	OGAP ≥ 0	OGAP < 0	OGAP≥ -0.97	OGAP< -0.97
Panel B: Coefficients on interactions with MPS (1994–2008)					
MPS x Whited-Wu	-1.60	-1.56	-1.57	-2.63	-0.90
	[-2.47]	[-0.82]	[-2.16]	[-2.75]	[-1.21]
MPS x Cash	-0.87	0.69	-1.06	0.15	-1.20
	[-2.12]	[0.48]	[-2.74]	[0.14]	[-2.90]
MPS x CF Duration	0.63	0.05	0.70	0.44	0.78
	[2.56]	[0.05]	[2.71]	[1.02]	[2.40]
MPS x CF Volatility	4.36	5.50	3.97	5.26	3.52
	[2.58]	[1.04]	[2.34]	[1.52]	[1.99]
MPS x Operating Profitability	-5.74	-19.58	-3.89	-15.28	-2.10
	[-2.02]	[-1.98]	[-1.46]	[-2.56]	[-0.76]
Firm FE	Yes	Yes	Yes	Yes	Yes
Meeting FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Industry FE × MPS	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes
Rating FE × MPS	Yes	Yes	Yes	Yes	Yes
Number of FOMC meetings	116	28	88	58	58
n	229,061	58,071	170,616	120,275	108,427
$\bar{R}^2(\%)$	15.99	7.95	20.06	17.77	14.55
Panel C: Average returns to MPE strategies (1975–2015)					
	(1)	(2)	(3)	(4)	(5)
(L)	1.30	1.15	1.32	0.83	1.45
	[5.08]	[1.75]	[4.75]	[2.23]	[4.34]
(2)	1.03	1.29	1.03	0.73	1.01
	[4.22]	[1.85]	[3.90]	[1.93]	[3.32]
(3)	0.87	1.11	0.75	0.92	0.98
	[3.84]	[1.77]	[3.09]	[2.51]	[3.68]
(4)	0.69	0.73	0.71	0.64	0.61
	[3.37]	[1.18]	[3.30]	[1.89]	[2.40]
(H)	0.53	0.83	0.53	0.68	0.47
	[2.58]	[1.09]	[2.47]	[1.90]	[1.84]
(L-H)	0.76	0.32	0.79	0.15	0.98
	[4.91]	[0.63]	[4.72]	[0.61]	[4.83]
Number of months	492	60	432	156	336

VIII Robustness to size of the firms in the sample

This section shows the robustness of the portfolio sort in Table 3 to the universe of stocks used in the portfolio sorts. Table VIII.1 shows results for three different size universes. Panel A reports the results from Panel A of Table 3. Panel B shows results for similarly constructed portfolios only for stocks that have market capitalization greater than the 20th percentile of NYSE in each month. Panel C shows results for similarly constructed portfolios only for stocks that have market capitalization greater than the 50th percentile of NYSE stocks in each month. The definitions of the size universes follow Fama and French (2008).

Naturally, the performance of the strategy decreases when we restrict the sample to the large-cap universe (Fama and French, 2008; Novy-Marx and Velikov, 2016). However, we can observe that the strategy continues to produce significant average returns to the long/short portfolio. Excluding microcaps yields 70 basis points per month (t-statistics of 4.97) and excluding small caps yields 53 basis points per month (t-statistic of 4.04). Even the Fama and French (2015) five-factor alpha for the large caps is a statistically significant 23 basis points per month (t-statistic of 2.03).

Table VIII.1
Returns to strategy in different size samples
This table reports average excess returns and alphas for portfolios constructed by sorting on the MPE index. In each month, firms are sorted by their monetary policy exposure (MPE) into quintiles based on NYSE breakpoints. MPE is estimated using equation (4) from the text. For each of the five portfolios, and for a portfolio long stocks with low MPE and short stocks with high MPE, average value-weighted returns in excess of the risk-free rate and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2015) five-factor model are reported. Panel A reports results for all firms, Panel B reports results for firms with market capitalizations larger than the 20$^{\text{th}}$ NYSE percentile, and Panel C reports results for stocks with market capitalizations larger than the NYSE median. T-statistics are in brackets. Sample period is 01/1975 to 12/2015.

Panel A: All firms						
	(L)	(2)	(3)	(4)	(H)	(L-H)
r^e	1.30	1.03	0.87	0.69	0.53	0.76
	[5.08]	[4.22]	[3.84]	[3.37]	[2.58]	[4.91]
α^{CAPM}	0.59	0.32	0.19	0.07	-0.11	0.69
	[4.56]	[3.12]	[2.39]	[1.03]	[-1.98]	[4.46]
α^{FF3}	0.37	0.18	0.11	0.04	0.01	0.36
	[4.42]	[2.13]	[1.41]	[0.58]	[0.17]	[3.73]
$\alpha^{\text{FF3+UMD}}$	0.53	0.30	0.18	0.06	-0.01	0.54
	[6.96]	[3.63]	[2.42]	[0.86]	[-0.11]	[5.97]
α^{FF5}	0.36	0.15	0.04	-0.04	-0.03	0.39
	[4.27]	[1.72]	[0.55]	[-0.66]	[-0.69]	[4.00]
Panel B: All but microcaps (market cap > 20% NYSE)						
	(L)	(2)	(3)	(4)	(H)	(L-H)
r^e	1.23	0.89	0.90	0.67	0.53	0.70
	[4.96]	[3.73]	[4.07]	[3.30]	[2.55]	[4.97]
α^{CAPM}	0.52	0.18	0.23	0.05	-0.11	0.63
	[4.67]	[1.98]	[3.03]	[0.79]	[-1.93]	[4.47]
α^{FF3}	0.35	0.07	0.18	0.04	0.01	0.34
	[4.26]	[0.84]	[2.32]	[0.71]	[0.29]	[3.45]
$\alpha^{\text{FF3+UMD}}$	0.45	0.18	0.23	0.05	-0.00	0.46
	[5.66]	[2.19]	[2.96]	[0.85]	[-0.01]	[4.77]
α^{FF5}	0.31	0.06	0.09	-0.05	-0.02	0.33
	[3.73]	[0.67]	[1.12]	[-0.81]	[-0.47]	[3.36]
Panel C: All but small (market cap > 50% NYSE)						
	(L)	(2)	(3)	(4)	(H)	(L-H)
r^e	1.04	0.91	0.79	0.59	0.51	0.53
	[4.45]	[4.17]	[3.81]	[2.94]	[2.42]	[4.04]
α^{CAPM}	0.36	0.26	0.17	-0.02	-0.13	0.49
	[3.72]	[3.19]	[2.27]	[-0.32]	[-2.03]	[3.67]
α^{FF3}	0.24	0.20	0.14	0.02	0.01	0.23
	[2.70]	[2.50]	[1.90]	[0.32]	[0.21]	[2.07]
$\alpha^{\text{FF3+UMD}}$	0.35	0.26	0.15	0.01	-0.01	0.35
	[3.95]	[3.10]	[1.95]	[0.20]	[-0.09]	[3.21]
α^{FF5}	0.22	0.11	0.04	-0.10	-0.01	0.23
	[2.41]	[1.29]	[0.51]	[-1.55]	[-0.19]	[2.03]