Monetary Policy Surprises, Investment Opportunities, and Asset Prices

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Abstract

I use changes in Federal funds futures rates on days of FOMC announcements to isolate monetary policy shocks. Recent evidence suggests that contractionary monetary policy shocks increase expected excess market returns. All else equal, standard intertemporal asset pricing theory predicts that these shocks should therefore earn a positive risk premium as long-lived investors will pay to hedge against decreases in expected returns. Consistent with this prediction, I find that a mimicking portfolio for these shocks earns positive average excess returns. Exposure to the monetary policy shock mimicking portfolio also jointly explains size, value, and momentum returns.

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1. Introduction

Asset prices have significant reactions to monetary policy announcements (See, e.g. Jensen and Johnson (1995), Kuttner (2001), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Hanson and Stein (2015), and Chava and Hsu (2015)). Bernanke and Kuttner (2005) attribute much of this price reaction to news of tighter monetary policy, such as unexpectedly high increases in Federal funds rates, increasing expected excess returns on stocks. Similarly, Gertler and Karadi (2015) and Hanson and Stein (2015) find that this news increases bond term and credit premia. Taken together, this evidence suggests that surprise changes in the Federal funds rate positively correlate with changes in the expected excess market return, and should therefore earn a positive risk premium in the cross-section of returns (see, e.g., Merton (1973)). However, several recent studies (see, e.g., Thorbecke (1997), Maio and Santa-Clara (2015), and Lioui and Maio (2014)) find that monthly or quarterly innovations in the Federal funds rate earn a negative risk premium.[1] In this paper, I attempt to reconcile these findings.

Most of the variation in the Federal funds rate is driven by the systematic response of the Federal Reserve to changes in the output gap and inflation, as prescribed by the rule of Taylor (1993), for example. Hence, Federal funds innovations capture both the systematic response of the Federal Reserve to innovations in economic conditions, as well as policy shocks, which are unexpected deviations from this systematic response. The systematic response of the Federal funds rate to innovations in economic conditions could earn a negative risk premium because the output gap and expected inflation negatively forecast returns and therefore investment opportunities (See, e.g., Fama (1975), Campbell (1996), Ang and Bekaert (2007), Cooper and Priestley (2009).). Federal funds policy shocks, which are unanticipated deviations of the Federal Reserve from its policy rule may command a positive risk premium, but be dwarfed by innovations in the business cycle and inflation.[2] Precisely identifying Federal funds policy shocks is therefore crucial to estimate their risk premium. This is important because identifying how monetary policy shocks impact asset

[1] The literature generally estimates a negative risk premium associated with innovations in other short-term interest rates as well. See, e.g., Brennan, Wang and Xia (2004) and Petkova (2006).

[2] Instead of "monetary policy shock", I use the term "Federal funds policy shock" to emphasize that they are derived from the Federal funds rate as opposed to a monetary aggregate like M0, M1, or M2. In particular, this makes a contractionary policy shock positive as opposed to negative.

prices is fundamental to understanding how monetary policy impacts the real economy.

Changes in Federal funds futures rates on days of Federal Open Market Committee (FOMC) announcements provide a precise measure of Federal funds policy shocks (see, e.g., Piazzesi and Swanson (2008)). Event studies, such as Kuttner (2001) and Bernanke and Kuttner (2005) use these to identify whether monetary policy shocks impact stock prices. I take advantage of this identification and relate these time-series impacts to the cross-section of returns via the Intertemporal Capital Asset Pricing Model (ICAPM. See, e.g., Merton (1973)). To do this, I form a mimicking portfolio, $FFED$, for the changes in the Federal funds futures rate relative to the day before FOMC announcements. If Federal funds policy shocks positively vary with investment opportunities, then this portfolio should earn a positive risk premium in the cross-section of returns. The use of a mimicking portfolio is necessary as these shocks are irregularly spaced around eight FOMC meetings per year. Using standard GMM stochastic discount factor methods, I test the power of a two-factor ICAPM with the market excess return (MKT) and $FFED$ to explain the average returns on the Fama-French 25 portfolios formed on size and book-to-market, and the 25 portfolios formed on size and momentum return.

My key results can be summarized as follows. $FFED$ earns a significant positive risk premium. Then, the two-factor ICAPM explains the returns on the 50 Fama-French portfolios with the same R^2 and lower mean absolute pricing error than the benchmark Fama-French-Carhart four-factor model. In a five-factor model with the Fama-French-Carhart four factors and $FFED$, only $FFED$ loads significantly in the discount factor, suggesting that the size, value and momentum factors do not add significant asset pricing power to $FFED$. In time-series regressions, controlling for exposure to $FFED$ eliminates the alphas earned by the value and momentum factors. Next, I find that the Federal funds rate no longer significantly forecasts stock returns (negatively) or volatility (positively) when controlling for the business cycle, as proxied by the output gap of Cooper and Priestley (2009), and inflation. Hence, innovations in the Federal funds rate that simply capture the systematic response of the Federal Reserve to changing economic conditions should command a negative risk premium. In particular, this can explain the negative risk premium on monthly or quarterly changes in the level of the Federal funds rate found by prior studies. Conversely, Federal funds policy shocks command a positive risk premium, consistent with prior evidence that expansionary monetary policy shocks adversely shift the investment opportunity set by lowering aggregate expected returns.

My study supports prior evidence that tighter monetary policy increases aggregate risk premia by empirically confirming the resulting cross-sectional implication from the ICAPM. My ICAPM approach allows for the precise identification of monetary policy shocks, while still testing whether they represent discount-rate or cash-flow news. In contrast, Bernanke and Kuttner (2005) and others frequently use vector autoregressions and Campbell and Shiller (1988)-type identities to decompose returns into cash-flow and discount-rate news. These decompositions lose the precise identification of FOMC announcement-day shocks by requiring regular time series that are only available at lower frequencies, such as monthly or quarterly. These decompositions also tend to produce unreliable estimates (see, e.g. Chen and Zhao (2009) and Maio (2014)). A second benefit to my approach is that it results in a single factor related to time-varying investment opportunities that explains both value and momentum returns, a novel result relative to the literature that tries to explain the cross-section of returns with the ICAPM.(See, e.g., Vassalou (2003), Brennan et al. (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Maio and Santa-Clara (2015).)

A third benefit to my approach is that it identifies a risk premium on Federal funds policy shocks, and the sign of this premium has implications for monetary policy. The Federal Reserve may try to increase aggregate demand via an expansionary monetary policy shock (see, e.g., Ludvigson, Steindel and Lettau (2002)). This shock may raise wealth by raising asset prices and present values, which would increase the consumption portion of aggregate demand, all else equal. However, estimating a positive risk premium on Federal funds policy shocks is evidence that the expansionary monetary policy shock also deteriorates the investment opportunity set, which, by definition, would decrease consumption per unit of wealth. The net result is an ambiguous impact of Federal funds policy shocks on consumption.

Several studies find noteworthy behavior of equity prices around FOMC and other macroeconomic announcements. Savor and Wilson (2014), for example, find that the CAPM prices a number of test assets well, but only on days of macroeconomic announcements including those from the

FOMC. My results are distinct from theirs in at least two ways. First, their CAPM results do not explain momentum returns, even on important announcement days. In contrast, my two-factor model does explain such returns. Second, my asset pricing results do not hold only on macroeconomic announcement days. Rather, my results are consistent with (i) investment opportunity set risk explaining value and momentum returns, and (ii) FOMC annoucements being an important (though not exclusive) source of news about investment opportunities. Lucca and Moench (2015) document that since 1994, over 80% of the equity premium is earned in the 24 hours prior to scheduled FOMC announcements. However, they find these pre-FOMC returns do not correlate with the Federal funds policy shocks that I study and conclude this phenomenon is distinct from the exposure of stocks to policy announcements. Cieslak, Morse and Vissing-Jorgensen (2014) find that since 1994, the entire equity risk premium is earned in weeks 0, 2, 4, and 6 relative to FOMC meetings.[3] They argue that this likely reflects a risk premium associated with information coming from the Federal Reserve, though it is not explained by the content of FOMC announcements, the shocks from which are the focus of this paper.

This paper is also related to the literature on financial intermediaries and asset prices. In the models of Drechsler, Savov and Schnabl (2014) and He and Krishnamurthy (2013), a reduction in the Federal funds rate can lower borrowing costs for relatively risk-tolerant financial intermediaries. This in turn allows intermediaries to bid up asset prices, lowering risk premia and Sharpe ratios. Adrian, Etula and Muir (2014) construct a mimicking portfolio, LMP, for intermediary leverage, arguing that intermediary leverage summarizes the pricing kernel of intermediaries. Given that monetary policy affects asset prices at least in part through intermediaries, I investigate whether intermediary leverage explains the returns on $FFED$. In a three factor model with MKT, LMP and $FFED$, all three factors significantly help to price assets. Hence, intermediary leverage alone does not seem to fully explain the effects of monetary policy shocks.

The remainder of the paper proceeds as follows. Section 2 describes my measures of monetary policy surprises and other data sources. Section 3 performs the core asset pricing tests with the futures-based Federal funds innovations. Section 4 discusses the contrast of my results and those

[3]The FOMC meets about every 6 weeks. Week 0 starts the day before an FOMC meeting.

from the previous literature. Section 5 presents several important robustness checks. Section 6 concludes.

2. Federal funds policy shocks and other data

2.1. Federal funds policy shocks

To make precise the meaning of "Federal funds policy shock", suppose the FOMC sets the Federal funds rate (FF) according to the rule of Taylor (1993):

$$FF_t = \alpha + \beta GAP_t + \gamma E_t(\pi_{t+1}) + u_t. \tag{1}$$

The output gap (GAP) equals the difference between real and potential real GDP, a common proxy for the state of the real business cycle, $E_t(\pi_{t+1})$ denotes expected inflation, and u_t denotes a policy deviation from the rule. Eq. (1) captures the Federal Reserve's statutory dual mandate of maximum employment and stable prices. A "monetary policy shock", or "Federal funds policy shock", ϵ_t^{FF}, is an innovation in u_t, that is $\epsilon_t^{FF} = u_t - E_{t-1}u_t$, where E_t denotes expectation with respect to publicly available information. Christiano, Eichenbaum and Evans (2005) among others generalize the Taylor rule in Eq. (1) to include other variables, however, the definition of monetary policy shocks remains the same and the simple rule given by Eq. (1) is sufficient for illustration purposes.

Since October 1988, the Chicago Mercantile Exchange has listed futures contracts, "Federal funds futures", that make a payment based on the Federal funds rate in a delivery month. Changes in these futures prices on days of FOMC announcements provide a very precise measure of Federal funds policy shocks because the futures market efficiently incorporates current macroeconomic conditions (see, e.g., Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), Piazzesi and Swanson (2008)). The primary alternative to using futures contracts to isolate monetary policy shocks is relying on some form of structural-identification-scheme in a vector autoregression (VAR) (see e.g., Christiano et al. (2005), or Christiano, Eichenbaum and Evans (1999) for a survey). Unfortunately, the choice of VAR specification tends to lead to qualitatively different responses of macroeconomic aggregates and asset prices to Federal funds policy shocks (see e.g., Cochrane and Piazzesi (2002), Uhlig (2005)). Survey expectations are also available for the Federal funds rate from sources such as Bloomberg, but they tend to have a limited history and a weekly timing that is somewhat inconvenient for asset pricing tests and prohibits the high-frequency identification associated with changes in Federal funds futures prices on FOMC days (see, e.g., Gilbert (2011)).

Federal funds futures make a payment equal to the interest on a notional amount of \$5 million, where the interest rate is given by the average (calendar) daily Federal funds rate over the delivery month. At any given time, there are 36 contracts outstanding, one for delivery in the current month, and one for delivery in each of the following 35 months. The price $P^n_{m,d}$ on day d, of month m for the contract with delivery in month $m+n$ is quoted as:

$$P^n_{m,d} = \$100 - f^n_{m,d}, \tag{2}$$

where $f^n_{m,d}$ denotes the futures rate. In this paper, I use the contracts with delivery in the current month ($n = 0$), and the following month ($n = 1$).

For a policy announcement on day d of month m, it is standard to isolate the policy shock from the change in the current-month futures rate, $f^0_{m,d}$. Federal funds futures prices equal the average Federal funds rate in the delivery month, so the change in the futures rate must be scaled up by a factor related to the number of days in the month affected by the change. As such, for all but the first calendar day of the month and last three calendar days of the month, I define the surprise change in the Federal funds rate on day d of month m by:

$$\Delta r^u_{m,d} \triangleq \frac{D_m}{D_m - d}\left(f^0_{m,d} - f^0_{m,d-1}\right), \tag{3}$$

where D_m denotes the number of calendar days in month m. For the first day of the month, the surprise equals the difference between the current-month futures rate and the one-month-ahead futures rate from the last day of the previous month $\Delta r^u_{m,1} \triangleq f^0_{m,1} - f^1_{m-1,D_{m-1}}$. For changes occurring in the last three days of the month, $\Delta r^u_{m,d} \triangleq f^1_{m,d} - f^1_{m,d-1}$, the change in the one-month-ahead futures rate.[4]

The set of Federal funds policy events consists of the union of regularly-scheduled FOMC meetings and any days of changes in the Federal funds target rate between regularly scheduled meetings. Regularly-scheduled meetings are not held in response to economic conditions, precluding endogeneity concerns for identifying policy shocks ex ante. Conversely, this is not necessarily the case for meetings that occur irregularly. However, stock prices fall in response to positive Federal funds announcement surprises on days of unscheduled FOMC announcements (see, e.g., Bernanke and Kuttner (2005)). As noted by Bernanke and Kuttner (2005), this mitigates endogeneity concerns that the futures based "policy shocks" represent news about economic conditions instead of true policy shocks because the FOMC would only raise the Federal funds rate in the presence of good news, which would raise stock prices in the absence of a policy shock.

To construct the sample, I start with the list of times when the outcome of policy events became known to financial markets from Kenneth Kuttner's website.[5] This set of events spans June 1989 through June 2008. I then extend this set through December 2008. The remainder of 2008 includes four regularly scheduled FOMC meetings with announcements made before closing time in the futures market. Finally, on October 7th, 2008, the FOMC decided to lower the Federal funds target by 50 basis point in a 5:30pm conference call, after the futures market had closed. Hence, I consider the change in futures price from October 7th to October 8th to derive the surprise. I do not measure policy shocks post-December 2008 as the Federal funds rate has been kept close to 0 since then.

2.2. Factor mimicking portfolio of policy shocks

The FOMC announcements are irregularly spaced so it is necessary to use a factor-mimicking portfolio to obtain a regular time series that has the same important risk characteristics as the announcement surprises. A mimicking portfolio is simply a regression of a factor onto a set of

[4] See Kuttner (2001) for a more detailed explanation of the precise construction of $\Delta r^u_{m,d}$.

[5] http://econ.williams.edu/people/knk1. Note that this sample includes an announcement on October 15, 1998 that occurred after the futures market closed. Following Bernanke and Kuttner (2005), I use the change in futures price from the close on the 15th to the open of the 16th to measure the surprise. Also, I obtained futures data from Bloomberg, however this study can be replicated using the futures-based data directly from Kuttner's website.

test asset returns. The slopes on the test assets correspond to weights in a portfolio with the same asset pricing information as the original factor, but the portfolio can be sampled at any frequency and in general will be more precisely measured than the factor itself (see, e.g., Cochrane (2005)). A tempting alternative approach to constructing a regular time series based on Federal funds policy shocks is to form a series that is 0 on non-announcement days and equal to the Federal funds policy shock on announcement days. This factor would be problematic in an ICAPM because investors care about the investment opportunity set that the Federal Reserve affects, not just FOMC announcements per se. There can be other news about the dimension of investment opportunities the Federal Reserve affects that can come at any time. Moreover, this alternative construction would impose the counterfactual assumption that there is no news about monetary policy on non-announcement days (see, e.g., Cieslak et al. (2014)).

As test assets, I use the 25 Fama-French size and book-to-market sorted portfolios and the Fama-French 25 size and momentum sorted portfolios, obtained from Kenneth French's website. A number of prior studies in the ICAPM literature use mimicking portfolios for macroeconomic factors to price the 25 size and book-to-market portfolios (see, e.g., Lettau and Ludvigson (2001), Vassalou (2003), Brennan et al. (2004) and Petkova (2006)). However, Lewellen, Nagel and Shanken (2010) find that these test assets are too easily priced by multi-factor models and recommend adding other test assets, such as those based on momentum sorts. A further reason to adding momentum-based assets to the 25 size and book-to-market portfolios is that Maio and Santa-Clara (2012) find that the Fama and French (1993) and Carhart (1997) size, value, and momentum factors most plausibly correspond to innovations in investment opportunities relative to other common factor models. This in turn suggests that spreads in size, value, and momentum most plausibly result from a spread in exposure to time-varying investment opportunities and therefore generate good sets of test assets to test an ICAPM model.

To form a mimicking portfolio for Federal funds surprises, I follow Breeden, Gibbons and Litzenberger (1989), Vassalou (2003), Ang, Hodrick, Xing and Zhang (2006), and Adrian et al. (2014) among others, and project the Federal funds policy shocks Δr_d^u onto a subset of eight base assets that summarize all 50 returns well. The eight base assets consist of the four "corners" from the 25

Fama-French size and book-to-market portfolios and the four "corners" from the Fama-French 25 size and momentum portfolios. These eight assets are highly representative of the 50 portfolios. In untabulated tests, the average correlation between the excess returns on the 50 portfolios chosen and their projections onto the eight base assets is over 0.95.

To be precise, let $szbm_{ijt}$ (szm_{ijt}) denote the excess return on the portfolio in the ith size quintile and the jth book-to-market (momentum) quintile on day or month t. I first estimate the regression:

$$\Delta r^u_d = a + X_d \cdot b + \epsilon_d, \tag{4}$$

where $X_d = (szbm_{11}, szbm_{15}, szbm_{51}, szbm_{55}, szm_{11}, szm_{15}, szm_{51}, szm_{55})'_d$. Then, for convenient scaling, I normalize the vector $\hat{b}$ to have length 1 so that the return on the mimicking portfolio, $FFED_m$, in month m is given by:

$$FFED_m = X_m \cdot \frac{\hat{b}}{||\hat{b}||}. \tag{5}$$

The precise weights for the mimicking portfolio are given by (t-statistics below in parentheses):

$$\frac{\hat{b}}{||\hat{b}||} = \begin{pmatrix} szbm_{11} & szbm_{15} & szbm_{51} & szbm_{55} & szm_{11} & szm_{15} & szm_{51} & szm_{55} \\ 0.05, & 0.85, & -0.09, & 0.01, & -0.48, & -0.16, & 0.09, & -0.07 \\ (0.21) & (3.11) & (-0.46) & (0.09) & (-2.50) & (-0.59) & (0.53) & (-0.84) \end{pmatrix}' \tag{6}$$

$FFED$ takes a large long position in small-value ($szbm_{15}$) and a relatively large short position in the small loser portfolio (szm_{11}). The correlation between $FFED_d$ and Δr^u_d is 0.38.[6] Moreover, a heteroskedasticity-robust Wald test rejects the null that $b = 0$ with a p-value of 0.002.

I sample $FFED$ over two time periods. The first period, 1989:1-2008:12, is the sampling period of the policy shocks. Then, I follow Campbell and Ammer (1993), Brennan et al. (2004), and other interest rate-based asset pricing studies and consider the longer sample period of 1952:1-2013:12. This is effectively the largest sample that follows the Treasury-Fed Accord of 1951, which re-established the independence of the Federal Reserve following the second World War. I extend

[6] The analogous correlation for a similar portfolio used in Adrian et al. (2014) is 0.37, for example.

$FFED$ out-of-sample over this entire long period using the weights given by Eq. (6).

2.3. Other data and descriptive statistics

Table 1 lists the main variables used in this paper along with their definitions and their respective sources.

INSERT TABLE 1 ABOUT HERE

Table 2 presents summary statistics of the important variables in the paper over two sample periods. The first sample period covers the existence of Δr^u, 1989:1-2008:12 (n=240). The second sample period covers the entire post-Treasury-Fed accord sample 1952:1-2013:12 (n=744). The future twelve-month inflation limits the sample for $\pi_{t+1,t+12}$ to 1951:1-2012:12, and the monthly Federal funds rate availability limits FF to 1954:7-2013:12.

INSERT TABLE 2 ABOUT HERE

In both sample periods, $FFED$ earned a positive risk premium, 77 basis points per month over 1989-2008 and 72 basis points per month over 1952-2013. The Federal funds policy shocks themselves were about -4 basis points on average during this sample period, consistent with a (potentially unexpected) general decline in the Federal funds rate during this period. Figure 1 presents a plot of the Federal funds policy shocks.

INSERT FIGURE 1 ABOUT HERE

Most of the shocks are close to zero consistent with relatively predictable monetary policy, however there are more negative surprises than positive ones. The largest surprise decrease of -74 basis points occured after an unscheduled meeting on January 21, 2008. The largest positive policy shock was 17 basis points, occuring on March 3, 2008, when the Fed failed to lower the target Federal funds rate as much as expected.

Other noteworthy features of the summary statistics include the average returns on the tradable risk factors. Over the 1989-2008 sample, the market excess return (MKT), the value factor (HML), and the momentum factor (MOM), earned average returns of about of 42, 29, and 97 basis points per month, respectively. Over the longer 1952-2013 sample, however, MKT, HML, and MOM earned average returns of 59, 36, and 75 basis points per month, respectively. SMB earned a relatively small 11 basis points in the shorter sample and 19 basis points per month in the longer sample.

3. Monetary policy shocks and asset prices

In this section, I present my main asset pricing results. Given the evidence that Federal funds policy shocks impact the market risk premium, and thus, the investment opportunity set, I use the framework of the ICAPM, expressed as the following discrete-time model of expected returns for an asset i (see, e.g., Cochrane (2005)):

$$E\left(R_{i,t+1}^{e}\right) = \beta_{iW}\lambda_W + \beta_{i\Delta z_t}'\lambda_z. \tag{7}$$

$R_{i,t}^{e}$ denotes the excess return on asset i, β_{iW} denotes the beta of asset i with respect to the excess return on the aggregate wealth portfolio, and $\beta_{i\Delta z_t}$ represents a vector of βs with respect to innovations in the state vector z_t. λ_W denotes the risk premium of the market portfolio, and λ_z denotes the vector of risk premia for each state variable.

To be of any hedging concern to investors, the state variables z_t must forecast returns or volatility of returns on the wealth portfolio (see, e.g., Maio and Santa-Clara (2012)). Long-lived investors will demand a premium in the form of higher expected returns to hold a security whose lowest returns coincide with adverse innovations in the state variables. Hence, if a state variable z_{jt} positively forecasts returns on the wealth portfolio, or negatively forecasts volatility, the risk premium, λ_{z_j} will be positive. I test the implication, based on the evidence that policy shocks postively correlate with changes in expected returns on the market, that $FFED$ commands a positive risk premium in a model of the form Eq. (7).

3.1. Time-series relationship of other asset pricing factors and *FFED*

Before presenting my main cross-sectional results, I follow Vassalou (2003) and investigate the correlation between $FFED$ and SMB, HML, and MOM, which are factors constructed to price portfolios formed on size, book-to-market and momentum as opposed to capture a particular economic factor. To do so, I estimate the following time-series regressions:

$$X_t = \alpha_X + \beta_{X,FFED} FFED_t + \epsilon_t,\ X = SMB,\ HML,\ MOM. \tag{8}$$

Table 3, Panels A and B presents the estimates of Eq. (8) for the 1989:1-2008:12 and 1952:1-2013:12 sample periods, respectively. In addition to assessing correlation, $FFED$ is a tradable excess return so I can test whether $FFED$ explains these factors by testing whether the intercepts are zero (see, e.g., Fama and French (1993), Cochrane (2005)). In order to test $FFED$ on factors that are not constructed from size and book-to-market and size and momentum portfolios, I also estimate Eq. (8) for the Fama and French (2015) investment and profitability factors (CMA and RMW, respectively).[7]

Insert Table 3 about here

The $FFED$ slopes of SMB, HML and UMD are relatively stable, positive and statistically significant in both sample periods. The most noteworthy result from Table 3 is that exposure to $FFED$ effectively eliminates the α earned by HML and MOM in both samples. Then, surprisingly, $FFED$ also seems to eliminate the significance of the α earned by the investment factor (CMA) in spite of the fact that CMA is constructed from totally different base assets as $FFED$.

One may suspect that these strong results could simply be attributable to forming $FFED$ from the particular eight base assets used. Given that the eight base assets used to make $FFED$ span the space of size, value and momentum returns, some combination of the base assets will price HML and UMD because the ex-post mean-variance efficient portfolio will always price every asset from this space in sample. However, what is interesting is that the weights on the base assets to make $FFED$ were not chosen to make it mean-variance efficient, they were chosen to have a maximum

[7] CMA and RMW come from the website of Kenneth French

correlation with Federal funds policy shocks. This economic content is what gives $FFED$ its asset pricing power (see, e.g., Breeden et al. (1989), Cochrane (2005)), not the choice of base assets.

In fact, random combinations of the base assets used to construct $FFED$ would fail to deliver this performance. In the Internet Appendix, I consider a simulation experiment to determine the likelihood that a randomly generated portfolio of the eight base assets used in $FFED$ would generate such strong results. Zero out of 10,000 simulated factors generate αs that are jointly as small or smaller than those on HML and MOM in Table 3. Hence, it is extremely unlikely that $FFED$ explains the returns on HML and MOM purely by chance. Overall, the time-series evidence presents a strong case that $FFED$ explains much of the risk premium associated with HML and MOM. In the next section, I consider the extent to which exposures to these two factors explain the cross-section of average stock returns.

3.2. GMM Results with *FFED*

Linear factor models such as Eq. (7) are equivalent (see, e.g., Brennan et al. (2004), Cochrane (2005)) to linear discount factor models of the form:

$$E\left(m_t R_t^e\right) = 0 \tag{9}$$
$$m_t = 1 + b' f_t.$$

$R_t^e = (R_{1t}^e, ..., R_{nt}^e)'$ denotes a vector of excess returns and f denotes a mean-0 vector of innovations in the market return and state variables. I test the canonical moment condition given by equation (9) via generalized method of moments (GMM) following Cochrane (2005).

Table 4 presents my main GMM tests with $FFED$. To estimate the discount factor coefficients (b), I use a one-step GMM estimation that equally weights pricing errors as my focus is explaining the variation in the size and book-to-market and size and momentum portfolios per se. The alternatives are multi-step procedures that give more weight to explaining returns on more statistically informative combinations of the underlying test assets. This leads to smaller asymptotic standard errors, but the results can be less-robust in sample (see, e.g. Cochrane (2005)). The risk premiums are implied by the discount-factor coefficients (see, e.g. Cochrane (2005), p. 108) and I compute standard errors for the risk premiums via the delta method.

Insert Table 4 about here

Following Cochrane (1996), Cochrane (2005), and Lioui and Maio (2014), among others I present three measures of overall model fit. First, I present mean absolute pricing errors for each model ($\overline{|\alpha|}$) based on the one-step estimation. The mean absolute pricing error is given by:

$$\overline{|\alpha|} = N^{-1}\sum_{i=1}^{N}|\alpha_i|, \tag{10}$$

where N is the number of assets and α_i denotes the pricing error of the i^{th} asset. The pricing error (α_i) can be interpreted as the difference between the average excess return on portfolio i ($\bar{R}_i^e$), and that implied by the estimated model ($-\text{Cov}_T(m_t, R_{it}^e)$):

$$\alpha_i = \left(T^{-1}\sum_{t=1}^{T}\hat{m}_t R_{it}^e\right) = \left(T^{-1}\sum_{t=1}^{T}R_{it}^e\right) - (-\text{Cov}_T(\hat{m}_t, R_{it}^e)), \tag{11}$$

where Cov_T denotes sample covariance.

As a second measure of model fit, I also present an OLS R^2 measure from a simple regression of average returns on factor βs with no constant:

$$\bar{R}_i^e = \beta_i'\lambda + \eta_i \tag{12}$$

I define:

$$R^2_{OLS} = 1 - \text{Var}_N(\eta_i)/\text{Var}_N(\bar{R}_i^e), \tag{13}$$

where $Var_N(x_i)$ denotes the cross-sectional variance of x_i. Note that using the variance instead of the second moment of R_i^e in Eq. (13) allows the R^2_{OLS} to be negative in the absence of a constant from the regression in Eq. (12). A negative R^2_{OLS} would indicate that the asset pricing model explains less of the cross-sectional variation of returns than a simple constant, and vice versa.

As a third measure of model fit, I also present the Hansen (1982) J test of the null that the pricing errors are jointly equal to 0 (over-identifying restrictions). The J statistic is given by:

$$J = T\alpha'_{2S}\hat{S}^{-1}\alpha_{2S} \sim \chi^2(N-K), \tag{14}$$

where K is the number of factors, $\hat{S}$ is the estimated covariance matrix of the average pricing errors (the "spectral density matrix"), and α_{2S} are the pricing errors from a two-step "efficient" GMM estimation where $\hat{S}^{-1}$ is the weighting matrix.

In Panels A and B, I compare the four factor model consisting of the Fama-French three factors and the Carhart momentum factor with the two-factor ICAPM consisting of MKT and $FFED$. In Panel A, I use the 1989:1-2008:12 sample period of the Federal funds futures market surprises. As expected, the Fama-French-Carhart model explains much of the cross-sectional variation in average returns over this sample with an R^2_{OLS} of 0.74 and a mean absolute pricing error ($\overline{|\alpha|}$) of 1.67% per annum. Further, MKT, HML, and MOM all have significant discount factor coefficients though the sample period seems too short to estimate statistically significant risk premiums.

Over the same sample period, the two-factor ICAPM achieves an R^2_{OLS} of 0.76, higher than that of the Fama-French-Carhart model, and has a lower $\overline{|\alpha|}$ of 1.57% per annum. The risk premium on $FFED$ is positive and significant as well. Overall, over 1989:1-2008:12, the two-factor ICAPM explains the spread in average returns on the 50 size and book-to-market and size and momentum portfolios about as well as the Fama-French-Carhart model. This conclusion is confirmed by the statistically indistinguishable J statistics across models. As is common in asset pricing models, the J statistic wildly rejects all models statistically.

Panel B also presents estimations of the Fama-French-Carhart model and the two-factor ICAPM, but over the 1952:1-2013:12 sample. The results appear similar to those in Panel A, but the longer sample period results in less noisy average returns and subsequently, more precise estimates. The Fama-French-Carhart model earns an R^2 of 0.81 and an $\overline{|\alpha|}$ of 1.17% per annum, whereas the two-factor ICAPM earns a very similar R^2 of 0.81 and a similar $\overline{|\alpha|}$ of 1.09% per annum. $FFED$ also earns a positive risk premium and a negative discount factor coefficient that are significant at the 1% level.

Panels A and B of Figure 2 present a plot of average returns versus those predicted by the

GMM estimates for the the two-factor ICAPM and Fama-French-Carhart models, respectively. These corresponds to the estimates in Panel B of Table 4. The two figures look very similar, although the two-factor ICAPM seems to have slightly smaller pricing errors in the non-extreme portfolios whereas the Fama-French-Carhart model seems to have smaller pricing errors on the smaller extreme growth portfolios $szbm_{21}$ and $szbm_{11}$.

Insert Figure 2 about here

$FFED$ was constructed from portfolios formed on size and book-to-market and size and momentum return. A natural question is whether the two-factor ICAPM prices just the size and book-to-market portfolios, or just the size and momentum portfolios, as well as the four factor model. Hence, Panels C and D of Figure 2 show plots of the average excess returns over 1952:1-2013:12 on the size and book-to-market portfolios versus those predicted by a one-step GMM estimation analogous to those from Table 4. The two-factor ICAPM explains the size and book-to-market with a lower R^2 of 0.61 versus 0.75 for the Fama-French-Carhart model. The two-factor ICAPM also has a larger pricing error on the small-growth portfolio, resulting in slightly higher $\overline{|\alpha|}$ of 1.08% per annum versus 0.98 for the Fama-French-Carhart model. Panels E and F of Figure 2 repeat the same exercise as Panels C and D, but with the size and momentum portfolios instead of the size and book-to-market portfolios. The two-factor model has lower pricing errors on most portfolios. The two-factor ICAPM earns a slightly higher R^2 of 0.92 versus 0.90 for the Fama-French-Carhart model, and a slightly lower $\overline{|\alpha|}$ of 0.97% per annum versus 1.13% per annum for the Fama-French-Carhart model. Overall, the two-factor ICAPM prices both sets of test assets well.

Panel C of Table 4 presents GMM estimates of equation (9) for the five-factor model with MKT, SMB, HML, MOM, and $FFED$. All of the discount factor coefficients besides that of $FFED$ are insignificant at the 10% level, whereas the coefficient for $FFED$ is still significant at the 1% level. Further, a χ^2-test fails to reject the hypothesis that the discount factor coefficients on SMB, HML, and MOM are jointly zero, at the 10% level. Overall, this is consistent with the Fama-French-Carhart factors not adding significant asset pricing information to $FFED$.

It is worth noting that every estimate of λ_{FFED} from the GMM estimations in Table 4 are within one standard error of the time series averages of $FFED$ in Table 2.[8] This helps to validate the point estimates in Table 4 by verifying that the cross-sectional model does not price the test assets only at the expense of deviating too far from the ex-post risk premiums (see, e.g. Cochrane (2005)) of the factors.

Given these strong results, I again investigate whether the choice of base assets used in $FFED$ drives the results. In the Internet Appendix, I present results from a simulation of factors based on the projection of random noise on the eight base assets I used to make $FFED$. In only 13 out of 10,000 (0.13%) such simulations do the simulated noise factors generate a t-statistic that is as great or greater than that on $FFED$ and t-statistics on SMB, HML and MOM that are less than or equal to those on MKT, SMB, HML and MOM presented in Panel E of Table 4. Similarly, only 25 out of 10,000 simulations generate factors that jointly have as high of R^2_{OLS} and as low of an $\overline{|\alpha|}$ as $FFED$. The simulations imply that $FFED$ almost certainly does not explain returns just by randomly choosing a lucky combination of the base assets. Rather, $FFED$ appears to derive its asset pricing power by reflecting the risk associated with Federal funds policy announcements. Moreover, many simulated $FFED$s even have a negative R^2_{OLS}. That is, they perform worse than a constant even though they are constructed from the extreme size and book-to-market and size and momentum portfolios.

Overall, the evidence in Tables 3-4 indicate that Federal funds policy shocks command a positive risk premium in equities and that $FFED$ explains returns on portfolios formed on size, value and momentum well. The Appendix also presents estimated β_{FFED}s for the test assets. The β_{FFED}s decrease with size, and increase with value and momentum return. Thus, given the positive risk premium from Table 4, one can visualize how the size, value and momentum premiums can be interpreted as compensation for exposure to the risk captured by $FFED$.

4. Contrast with prior literature

The evidence above indicates that Federal funds policy shocks have a positive risk premium. In this section, I investigate ICAPM-based explanations for why prior literature finds a negative risk

[8] This can be seen by inverting the t-statistics in Table 4

premium on monthly or quarterly innovations in the Federal funds rate. The level of the Federal funds rate negatively forecasts market returns and positively forecasts volatility, so its innovations should earn a negative risk premium in the cross-section of returns, all else equal. However, if the FOMC sets the Federal funds rate according to the rule given by Eq. (1), then the Federal funds rate could simply inherit its negative forecasting power for returns from the business cycle and inflation. If this is the case, then monthly or quarterly Federal funds innovations could simply proxy for innovations in the business cycle and inflation, which dominate the policy shock portion of the innovation, earning a negative risk premium as a result. Hence, I test whether the the business cycle and inflation explains the forecasting relationship between the Federal funds rate and the investment opportunity set.

To do this, Table 5 presents forecasting regressions of the form:

$$r_{t+1,t+h} = \alpha + \beta' X_t + \epsilon_{t+1,t+h}, \tag{15}$$

where $r_{t+1,t+h}$ denotes the log excess returns on the CRSP value-weighted index over months $t+1$ through $t+h$. In Panel A, X_t includes FF and $\log(D/P)$, the Federal funds rate and log dividend-price ratio on the CRSP value weighted stock index, respectively. I include $\log(D/P)$ following Ang and Bekaert (2007) as I find in untabulated tests that the Federal funds rate has at most marginally significant forecasting power without controlling for the dividend yield. In Panel B, X_t also includes GAP and $\pi_{t-12,t}$, the output gap of Cooper and Priestley (2009)[9] and log-inflation over the 12 months ending in month t, respectively. Following Ang and Bekaert (2007) and Brogaard and Detzel (2015), I use Hodrick (1992) standard errors.

Insert Table 5 about here

Panel A shows that the Federal funds rate is a significant, negative forecaster of returns. However, Panel B shows that adding GAP and $\pi_{t-12,t}$ eliminates the significance of the Federal funds rate in forecasting returns. Though insignificant, the slope on FF remains negative. This should not be considered evidence that policy shocks negatively forecast returns. GAP and $\pi_{t-12,t}$ are imprecisely

[9] GAP denotes log industrial production with a quadratic time-trend removed. Monthly measures of output generally rely on Industrial Production as GDP is only available quarterly.

measured proxies of the variables in the monetary policy rule given by Eq. (1). Hence, GAP and $\pi_{t-12,t}$ will not perfectly capture all of the variation in the precisely measured, market-based FF. Moreover, any other business cycle and inflation measures that the Federal Reserve responds that are absent from the Taylor rule specified in Eq. (1) further exacerbate this problem.

The Federal funds rate may also relate to another important dimension of investment opportunities, the volatility of the market return (see, e.g., Maio and Santa-Clara (2012)). Hence, following Maio and Santa-Clara (2012) I consider similar tests as those in Table 5, but with the variance of the market return as the dependent variable. Table 6 presents the variance forecasting regressions, which take the form:

$$VAR_{t+1,t+h} = \alpha + \beta' X_t + \epsilon_{t+1,t+h}, \tag{16}$$

where $VAR_{t+1,t+h} = VAR_{t+1} + ... + VAR_{t+h}$ and VAR_t is the variance of daily returns on the CRSP value-weighted index in month t.

Insert Table 6 about here

Panel A shows that the Federal funds rate is a significant predictor of variance at the 12-month horizon. However, Panel B shows that, like returns, adding GAP and $\pi_{t-12,t}$ eliminates the significance of the Federal funds rate in forecasting return variance.

Overall, the evidence from Tables 5 and 6 is consistent with business cycle and inflation driving the relationship between the level of the Federal funds rate and the investment opportunity set. Hence, if innovations in the Federal funds rate earn a negative risk premium, they seem to do so because they capture innovations in the business cycle or inflation as opposed to policy shocks.

5. Robustness

In this section I discuss the robustness of my main results that Federal funds policy shocks command a positive risk premium and price sorts on size, value and momentum.

5.1. Federal funds risk during the zero lower bound period

$FFED$ was formed using all available policy shocks over the 1989-2008 sample. During this sample and the extended 1952:1-2013:12 sample, $FFED$ prices assets well, suggesting that the asset pricing power of $FFED$ is stable. However, one may seek reassurance of the stability of the relationship between $FFED$ and the asset pricing news captured by monetary policy shocks. A recent quasi-experiment provides at least some opportunity for such reassurance. In December 2008, the Federal Reserve replaced the single Federal funds target rate with a range of 0 to 25 basis points. This so-called "zero lower bound" remains through the end of the sample. During this period, risk associated with large changes in the Federal funds rate, particularly decreases, was minimal. Hence, the risk premium earned by $FFED$ should be less during this period.

To investigate, I compare the returns on $FFED$ over the 60 zero-lower-bound months of the sample (2009:1-2013:12) to those from the 60 months leading up to this period. Table 7 presents estimations of two CAPMs with $FFED$ as the dependent excess return. Controlling for just the market factor as the CAPM does leaves the average return attributable to the hedging risk portion of the ICAPM (the $\beta'_{i,\Delta z}\lambda_z$ portion of Eq. (7)). In Column (1) the sample is the 60 months prior to the institution of the zero lower bound (2004:1-2008:12) and in Column (2) the sample is the 60 zero-lower-bound months (2009:1-2013:12).

Insert Table 7 about here

In the 60 months prior to the institution of the zero lower bound, $FFED$ earned a sizable CAPM α of about 50 basis points per month (6% p.a.). However, in the 60 zero-lower-bound months $FFED$ effectively earned a CAPM α of zero. A standard robust Wald test (untabulated) rejects at the 5% level the null that CAPM α of $FFED$ was not greater prior to the zero-lower-bound period.[10] These patterns are consistent with $FFED$ capturing low Federal funds risk during the out-of-sample zero-lower-bound period and earning a commensurate risk premium of 0.

[10]This is a one-sided test. The corresponding test with a two-sided alternative is significant at the 10% level.

5.2. *FFED* and factors related to Federal funds rate

The forecasting regressions in Tables 5 and 6 indicate, via the ICAPM, that the negative risk premium on innovations in the Federal funds rate comes from the business cycle and inflation rather than policy shocks. Rather than only rely on this ICAPM implication, I directly verify that monthly innovations in the Federal funds rate and related factors do not explain the asset pricing power of $FFED$ in the cross-section of returns. I do this by forming mimicking portfolios for factors related to monetary policy shocks, constructed from the same set of base assets as $FFED$, and investigating whether they can explain the asset pricing results in Section 3. This has the additional benefit of providing further evidence that the asset pricing power of $FFED$ does not simply come from the choice of base assets used in its construction.

I generate the mimicking portfolios for the several factors related to the Federal funds rate by estimating the following:

$$\Delta r_{rt} = a^{r_r} + X_t \cdot b^{r_r} + \Delta r_{r,t-1} \cdot c^{r_r} + \epsilon_t^{r_r} \tag{17}$$

$$\Delta BILL_t = a^{BILL} + X_t \cdot b^{BILL} + \Delta BILL_{t-1} \cdot c^{BILL} + \epsilon_t^{BILL} \tag{18}$$

$$\Delta \overline{FF}_t = a^{FF} + X_t \cdot b^{FF} + \Delta FF_{t-1} \cdot c^{FF} + \epsilon_t^{FF} \tag{19}$$

$$\pi_{t+1,t+12} = a^{\pi} + X_t \cdot b^{\pi} + \pi_{t-12,t-1} \cdot c^{\pi} + \epsilon_t^{\pi} \tag{20}$$

X_t denotes the same set of test assets as in Eq. (4) but at the monthly frequency. The lagged macro variables in Eqs. (17)-(20) control for predictable variation in the macro variable allowing the loadings on the base assets to more cleanly reflect innovations in the variables (see, e.g. Vassalou (2003)). To get the most precise estimates on the b's, the sample period for equations (17)-(20) span 1952:1 through 2013:12 unless limited by data constraints. $\pi_{t+1,t+12}$ limits the sample period to end in 2012:12 in equation (20) and FF limits the sample period to start in July 1954 in equation (19). The four respective mimicking portfolios are given by:

$$F_{Z,t} = X_t \cdot \hat{b}^Z, Z = r_r, BILL, FF, \pi_{t+1,t+12} \tag{21}$$

Panels A and B of Table 8 present one-step and two-step GMM estimates, respectively, of the model given by Eq. (9) with factors MKT, $FFED$, F_{BILL}, F_{FF}, F_{r_r}, and F_π. The test assets include all 50 size and book-to-market and size and momentum portfolios.

Insert Table 8 about here

The replicating portfolios for the changes in $BILL$ and FF earn a negative risk premium, consistent with the aforementioned prior literature. F_π does as well. However, the real interest rate replicating portfolio earns a positive risk premium, consistent with the ICAPM but in contrast with the negative risk premium found by Brennan et al. (2004). Most importantly, the interest rate and inflation factors do not subsume the explanatory power of $FFED$ as none of the discount factor coefficients besides $FFED$'s are significant in one-step or two-step estimation.

5.3. Signaling and uncertainty

Federal funds policy shocks could command a positive risk premium because they reflect a signal that the Fed has more optimistic expectations about the future path of the economy than does the market. This is consistent with Romer and Romer (2000) who find that the Federal Reserve possesses a private forecast of inflation and output that is not subsumed by commercially available forecasts. However, this view is hard to reconcile with the fact that stock prices fall in response to positive Federal funds policy shocks. Boyd, Hu and Jagannathan (2005) argue that stocks can fall in response to good news, because this news increases expectations of future interest rates. However, Bernanke and Kuttner (2005) find a very small impact of monetary policy shocks on expected future interest rates.

Bekaert, Hoerova and Lo Duca (2013) find that Federal funds policy shocks positively correlate with uncertainty, proxied by the VIX index. Increasing risk could explain why Bernanke and Kuttner (2005) find that positive Federal funds shocks increase the equity risk premium. However, VIX commands a negative risk premium (see, e.g., Ang et al. (2006)) as risk and uncertainty adversely affect the investment opportunity set. If tighter monetary policy increases the equity risk premium only by increasing the quantity of risk, then Federal funds policy shocks should command a negative risk premium, counter to my results. Rather, my results are consistent with tighter monetary policy increasing the market Sharpe ratio via increasing expected returns on the market. Similarly, Pástor and Veronesi (2013) shows that policy uncertainty can increase the equity risk premium. Hence, positive Federal funds policy shocks could correlate with increased policy uncertainty as well. However, policy uncertainty also commands a negative price of risk (see, e.g., Brogaard and Detzel (2015)). Hence, the effect of monetary policy shocks on stock prices does not appear to come from effects on risk or uncertainty.

5.4. Intermediaries

Monetary policy works directly through financial intermediaries in executing its open market operations. Hence, one likely explanation for my results comes from the recent literature on intermediary based asset pricing that posits a relationship between monetary policy and aggregate expected returns. He and Krishnamurthy (2013) and Drechsler et al. (2014) present models in which a reduction of the Federal funds rate increases the ability of relatively risk tolerant financial intermediaries to bid up asset prices, lowering risk premia and Sharpe ratios.

Adrian et al. (2014) argue that the leverage of the intermediary sector should be a state variable that describes the pricing kernel of intermediaries. They construct a mimicking portfolio, LMP for intermediary leverage in a comparable fashion as $FFED$. The two factors have qualitative differences in their loadings on the base assets. $FFED$ is dominated by positions in small-cap portfolios whereas LMP does not have a strong size tilt. Further, LMP has a large negative weight in growth stocks whereas $FFED$ does not have a significant position in growth.[11] Nonetheless, given the likely relationship of Federal funds risk with the intermediary channel, I test whether LMP explains the asset pricing power of $FFED$. Panels A and B of Table 9 present one-step and two-step GMM estimates, respectively, of the models with factors MKT and LMP, and MKT, $FFED$, and LMP.

Insert Table 9 about here

[11] They only use the momentum factor as opposed to four size momentum portfolios, and use the 6 size and book-to-market portfolios, as opposed to the four extreme portfolios from the 25 size-value portfolios, slightly limiting the comparison. However, in untabulated results I verify that the comparison I make still holds if I construct FFED with the same portfolios they use.

MKT and LMP alone explain 57% of the variation in average returns on the 50 portfolios, with LMP earning a significant risk premium. Adding $FFED$ increases the R^2 further to 0.85 and reduces the mean absolute pricing error from 1.78% per annum to 1.00%.[12] In one-step estimation LMP does not have a significant discount factor coefficient in the presence of $FFED$, but in two step estimation, both factors have significant discount factor coefficients, suggesting that both factors help to price assets. In particular, Table 9 is evidence against the null that intermediary leverage explains the returns associated with Federal funds policy risk. Hence, the intermediary channel does not yet appear to fully explain the risk premium of $FFED$.

5.5. Additional results in the Internet Appendix

Aside from the simulations and factor loadings described in Section 3, the Internet Appendix contains two additional robustness results and a detailed review of related literature.

The first of the two robustness checks verifies that there is a positive risk premium on the monthly frequency measure (BK) that Bernanke and Kuttner (2005) uses to relate monetary policy to expected returns. I perform this check via sorting common stocks into portfolios based on estimated exposure to BK and observing that average returns as well as CAPM and Fama and French (1993)-three factor alphas increase monotonically with exposure to BK. This is consistent with my evidence of a positive risk premium on Federal funds policy shocks. However, BK suffers from several sources of noise and endogenous variation, discussed further in the Internet Appendix, so I do not rely on it for my main results.

The second robustness check shows how vector autoregression (VAR)-based identification can fail to produce Federal funds policy shocks that are truly independent of business cycle and inflation shocks, even if they are all mutually orthogonal in sample. Thorbecke (1997) uses a structural VAR to isolate monthly Federal funds policy shocks that are orthogonalized with respect to industrial production and inflation shocks and finds a negative risk premium on the Federal funds shocks. However, I estimate several ICAPMs and find that these Federal funds shocks only have a negative risk premium in the absence of the industrial production shocks. That is, these Federal funds

[12] In untabulated tests, the results are qualitatively similar when I construct $FFED$ with exactly the same base assets as used for LMP.

shocks seem to inherit a negative risk premium from production shocks in spite of the in-sample orthogonalization.

6. Conclusion

Monetary policy has a large impact on asset prices, though the asset pricing implications of exposure to monetary policy are not completely understood. I use futures contracts to isolate Federal funds policy shocks and find that, contrary to the existing evidence, these shocks command a positive risk premium in the cross-section of stock returns. Moreover, a two-factor model with the market excess return and a portfolio that mimics Federal funds policy shocks prices the cross section of returns well. This evidence is consistent with that of Bernanke and Kuttner (2005) that expansionary Federal funds policy shocks decrease aggregate expected excess returns, adversely impacting the investment opportunity set. I also find that the level of the Federal funds rate negatively relates to investment opportunities, but only because it captures the business cycle and inflation, which the Federal Reserve reacts to. As a result, previously used measures of Federal funds innovations seem to earn a negative risk premium because they capture changes in economic conditions, not shocks to monetary policy.

This evidence has consequences for monetary policy. In the standard textbook treatment (see, e.g., Mankiw (2016)), the Federal Reserve attempts to use expansionary monetary policy to increase aggregate demand. The Federal Reserve may increase wealth via an expansionary monetary policy shock that raises asset prices. By itself, this would increase the consumption portion of aggregate demand. However, the evidence in this work indicates that even if an expansionary monetary policy shock increases wealth, it also adversely affects the investment opportunity set for this wealth, which has a countervailing effect on consumption. It then follows that the net effect of a monetary policy shock on consumption is ambiguous.

There is still an unanswered question of how monetary policy affects the equity risk premium. The positive risk premium I estimate on Federal funds policy shocks is inconsistent with tighter monetary policy simply increasing risk through such channels as weakening balance sheets of firms (see, e.g., Bernanke and Gertler (1995)) or increasing policy uncertainty. The more likely possibility is that Federal funds policy affects risk premia through the financial intermediary channel. In these models (see, e.g., Drechsler et al. (2014) and He and Krishnamurthy (2013)), a reduction in the Federal funds rate allows relatively risk tolerant intermediaries to increase their leverage and bid up asset prices, lowering risk premia and Sharpe Ratios, adversely affecting investment opportunities. This is consistent with the positive risk premium I estimate on Federal funds policy shocks. However, I find that a mimicking portfolio for intermediary leverage, a key state variable in intermediary asset pricing (see, e.g., Adrian et al. (2014)) fails to explain the returns on my Federal funds policy shock portfolio. Thus, intermediary asset pricing currently provides at most an incomplete theory of how monetary policy affects risk premia. Future research is needed to furnish such a complete theory.

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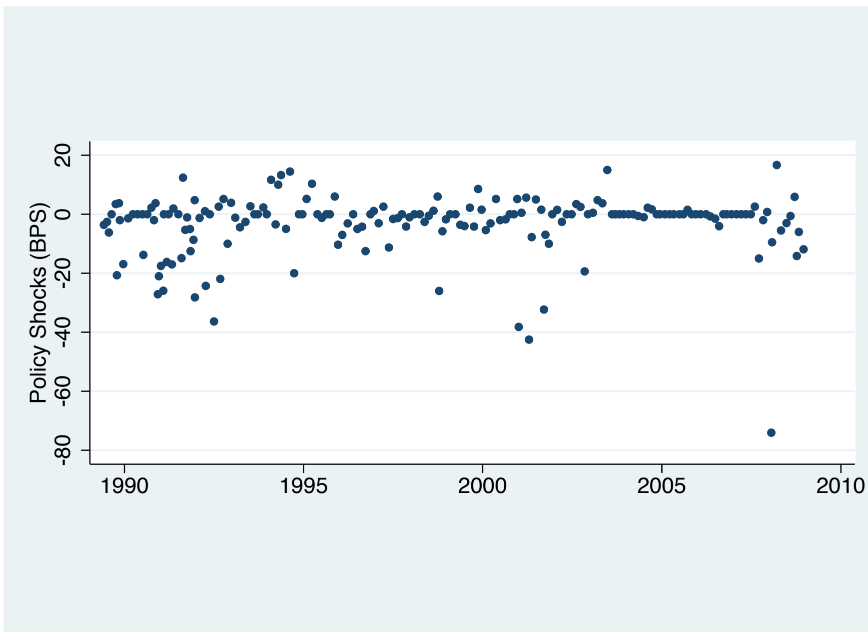
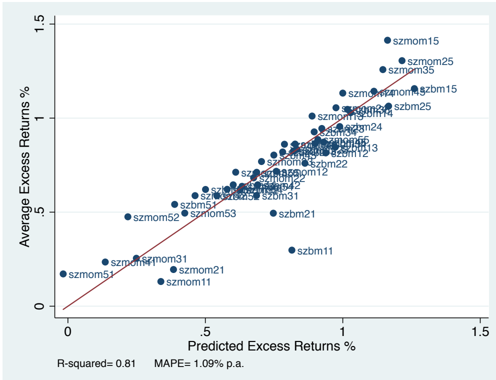
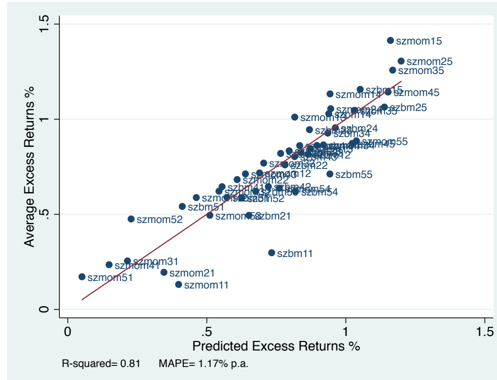


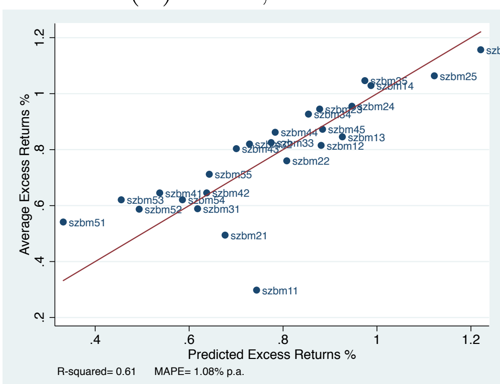
Figure 1: Federal funds policy shocks.
This figure depicts the 182 Federal funds policy shocks (Δr^u) based on changes in Federal funds futures rates on days of FOMC announcements from Jun 5, 1989 through December 16, 2008.



(A) MKT, $FFED$

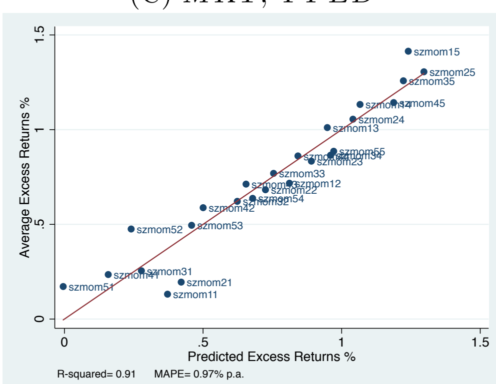


(B) MKT, SMB, HML, MOM

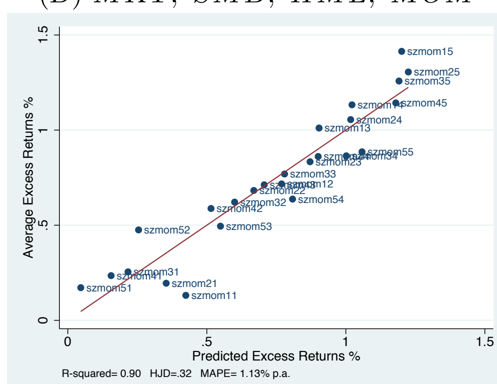


(C) MKT, $FFED$

(D) MKT, SMB, HML, MOM



(E) MKT, $FFED$



(F) MKT, SMB, HML, MOM

Figure 2: Predicted vs. actual average excess returns from one-step GMM estimations of two linear pricing kernel models for three different sets of assets.

In the left panels, the factors are MKT, $FFED$ and in the right panels they are MKT, SMB, HML, MOM. Panels (A) and (B) show results for the 25 size and book-to-market and 25 size and momentum portfolios. Panels (C) and (D) ((E) and (F)) show estimates form just the size and book-to-market (size and momentum portfolios) portfolios.

Table 1: Variable definitions

Name	Definition	Source
$szbm_{ij}$	Excess return on the portfolio in the ith size quintile and jth Book-to-Market quintile from the Fama French 25 Size and Book-to-Market Sorted Portfolios	Kenneth French Website
szm_{ij}	Excess return on the portfolio in the ith size quintile and jth Momentum quintile from the Fama French 25 Size and Momentum Sorted Portfolios	Kenneth French Website
MKT	Excess Return on the CRSP Value-Weighted Index	Wharton Research Data Services (WRDS)
SMB	Fama and French (1993) size factor	WRDS
HML	Fama and French (1993) value factor	WRDS
MOM	Carhart (1997) momentum factor	WRDS
CPI	Consumer Price Index (CPI)	St Louis Federal Reserve Website (FRED)
$\pi_{t+1,t+12}$	Change in log CPI over months $t+1$ to $t+12$	FRED
r_r	Real 1-month bill rate: log one-month Treasury bill yield minus the first difference in $\log(CPI)$	WRDS and FRED
$BILL$	Yield on the 3-month treasury bill	FRED
FF	Effective federal funds rate (Note that the monthly frequency FF on FRED is the average calender daily effective federal funds rate)	FRED
GAP	Monthly output gap of Cooper and Priestley (2009) formed by removing a quadratic time trend from the natural log of the Industrial Production Index	FRED

Table 2: Summary statistics

This table presents means, standard deviations, minimums and maximums of the variables used in the paper. MKT denotes the excess return on the CRSP value-weighted index, SMB and HML are the Fama French size and value factors, MOM denotes the Carhart (1997) momentum factor. Δr_d^u denotes the federal funds policy shock on day d. r_r denotes the real log 1-month bill rate. π denotes the one-month change in $\log(CPI)$ and $\pi_{t+1,t+12}$ denotes the change in $\log(CPI)$ over the following 12 months. FF denotes the effective federal funds rate (APR). The frequency of all variables is monthly, except for Δr_d^u, which has 182 daily observations. In Panel A, the sample is 1989:1-2008:12 (n = 240). In Panel B, the sample is 1952:1-2013:12 (n = 744 months), with one exception. The sample for which $\pi_{t+1,t+12}$ is available is 1952:1-2012:12.

Panel A: 1989-2008				
	Mean	Std. Dev.	Min	Max
MKT	0.42%	4.28%	-17.23%	10.83%
SMB	0.11%	3.49%	-16.39%	22.00%
HML	0.29%	3.19%	-12.60%	13.84%
MOM	0.97%	4.63%	-24.97%	18.39%
$FFED$	0.77%	2.39%	-15.79%	9.02%
FF	4.50%	2.14%	0.16%	9.85%
Δr_d^u	-0.04%	0.11%	-0.74%	0.17%
r_r	0.11%	0.29%	-1.08%	1.82%
π	0.24%	0.28%	-1.79%	1.37%
Panel B: 1952-2013				
	Mean	Std. Dev.	Min	Max
MKT	0.59%	4.33%	-23.24%	16.10%
SMB	0.19%	2.90%	-16.39%	22.02%
HML	0.36%	2.71%	-12.68%	13.87%
MOM	0.74%	3.97%	-34.72%	18.39%
$FFED$	0.72%	2.06%	-15.79%	10.81%
$BILL$	4.58%	3.02%	0.01%	16.30%
FF	5.16%	3.54%	0.07%	19.10%
r_r	0.08%	0.28%	-1.09%	1.82%
π	0.29%	0.31%	-1.79%	1.79%
$\pi_{t+1,t+12}$	3.52%	3.65%	-20.51%	19.73%

Table 3: Size, value, momentum, investment, and profitability returns controlling for $FFED$

This table presents estimates from time-series regressions of the form: $r_{it} = \alpha_i + \beta_i FFED_t + \epsilon_{it}$. Each i denotes one of the following: SMB, HML, MOM, CMA, or RMW. In Panel A, the sample spans 1989:1-2008:12 (n=240). In Panel B, the sample is 1952:1-2013:12 (n=744), except for CMA and RMW, which are only available since 1963. Parentheses below the estimates present OLS t-statistics. The constant term is in units of % per month. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A: 1989:1-2008:12

	SMB	HML	MOM	CMA	RMW
α	-0.03	-0.15	0.07	0.06	0.28
	(2.12)	(-0.77)	(0.27)	(0.39)	(1.51)
$FFED$	0.19**	0.57***	1.18***	0.34***	0.21***
	(2.08)	(7.24)	(11.90)	(6.21)	(2.77)
N	240	240	240	240	240
R^2	0.02	0.18	0.37	0.14	0.03

Panel B: 1952:1-2013:12

	SMB	HML	MOM	CMA	RMW
α	-0.07	0.01	0.00	0.11	0.23**
	(-0.67)	(0.09)	(0.03)	(1.33)	(2.43)
$FFED$	0.36***	0.48***	1.02***	0.29***	0.04
	(7.28)	(10.73)	(16.89)	(8.26)	(1.04)
N	744	744	744	606	606
R^2	0.07	0.13	0.28	0.10	0.00

Table 4: GMM tests with FFED

This table presents one-step GMM estimations of several linear pricing kernel models. The test assets are the excess returns on the Fama French 25 portfolios formed on size and book-to-market and the 25 portfolios formed on size and momentum. In Panels A and B, the first five columns present estimates with factors MKT, SMB, HML, and MOM, and the last three columns present estimates with factors MKT and $FFED$. In Panel C, the factors are MKT, SMB, HML, MOM, and $FFED$. b and λ denote the discount factor coefficients and risk premiums, respectively, for each factor. R^2_{OLS} denotes the R^2 from the OLS cross-sectional regression of average returns on βs defined in section 3, and $|\alpha|$ denotes the mean absolute pricing errors per annum. J denotes the Hansen (1982) J test statistic and p-values are next to the Js in parentheses. $\chi^2\,(b_{smb}, b_{hml}, b_{umd})$ and p_{χ^2} denote the χ^2-test statistic and p-value, respectively, of the test that the discount factor coefficients on SMB, HML and MOM are jointly 0. In Panel A, the sample is 1989:1-2008:12. In Panels B and C, the sample is 1952:1-2013:12. Newey and West (1987) t-statistics based on three lags of serial correlation are in parentheses.

Panel A: 1989:1-2008:12							
	MKT	SMB	HML	MOM		MKT	$FFED$
b	-0.06	-0.02	-0.09	-0.06	b	-0.03	-0.16
$t(b)$	(-2.50)	(-0.83)	(-2.94)	(-2.72)	$t(b)$	(-1.41)	(-3.22)
λ	0.44	0.13	0.37	0.99	λ	0.40	0.86
t_λ	(1.17)	(0.45)	(1.62)	(2.19)	t_λ	(0.89)	(3.02)
R^2_{OLS} =0.74, $\overline{\lvert\alpha\rvert}$ =1.67, J =153(0.00)					R^2_{OLS} =0.76, $\overline{\lvert\alpha\rvert}$ =1.57, J =113(0.00)		
Panel B: 1952:1-2013:12							
	MKT	SMB	HML	MOM		MKT	$FFED$
b	-0.05	-0.02	-0.10	-0.07	b	-0.02	-0.19
$t(b)$	(-4.36)	(-1.35)	(-5.19)	(-4.28)	$t(b)$	(-1.41)	(-4.58)
λ	0.62	0.17	0.42	0.82	λ	0.56	0.81
t_λ	(2.84)	(1.19)	(3.44)	(3.33)	t_λ	(2.14)	(4.80)
R^2_{OLS} =0.81, $\overline{\lvert\alpha\rvert}$ =1.17, J =218(0.00)					R^2_{OLS} =0.81, $\overline{\lvert\alpha\rvert}$ =1.09, J =158(0.00)		

Panel C: 1952:1-2013:12					
	MKT	SMB	HML	MOM	$FFED$
b	-0.02	0.04	0.04	0.03	-0.28
$t(b)$	(-1.05)	(1.30)	(1.12)	(1.32)	(-3.42)
λ	0.63	0.24	0.35	0.77	0.93
t_λ	(2.67)	(1.58)	(2.74)	(2.41)	(4.72)
R^2_{OLS} =0.87, $\overline{\lvert\alpha\rvert}$ =0.91, J =147(0.00)					
$\chi^2\,(b_{SMB}, b_{HML}, b_{MOM})$=2.15, p_{χ^2} = 0.54					

Table 5: Forecasts of log excess returns on the stock market with the Federal funds rate: with and without output gap and inflation

This table presents forecasting regressions of the form: $r_{t+1,t+h} = \alpha + \beta' X_t + \epsilon_{t+1,t+h}$, where $r_{t+1,t+h}$ denotes the log excess return on the CRSP value-weighted index over months $t+1$ through $t+h$. In Panel A, X_t includes FF and $\log(D/P)$, the Fed funds rate and log dividend-price ratio on the CRSP value weighted stock index, respectively. In Panel B, X_t also includes GAP and $\pi_{t-12,t}$, the output gap of Cooper and Priestley (2009) and log-inflation over the 12 months ending in month t, respectively. The sample period is 1954:8-2013:12. t-statistics based on Hodrick (1992) standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Forecasts with FF and $\log(D/P)$				
	h=1	h=3	h=6	h=12
FF	-0.12**	-0.51***	-0.86***	-1.43**
	(-2.21)	(-3.05)	(-2.67)	(-2.32)
$\log(D/P)$	1.63***	4.62***	8.38***	14.40**
	(3.08)	(2.93)	(2.70)	(2.34)
N	713	711	708	702
adj-R^2	0.01	0.05	0.08	0.11
Panel B: Forecasts with FF, $\log(D/P)$, GAP, and $\pi_{t-12,t}$				
	h=1	h=3	h=6	h=12
FF	-0.04	-0.27	-0.40	-0.97
	(-0.51)	(-1.19)	(-0.90)	(-1.16)
$\log(D/P)$	1.23**	3.15*	5.15	7.25
	(2.07)	(1.81)	(1.51)	(1.09)
GAP	-5.08*	-17.62**	-37.71**	-75.85**
	(-1.86)	(-2.19)	(-2.33)	(-2.36)
$\pi_{t-12,t}$	-9.48	-22.75	-38.47	7.94
	(-0.86)	(-0.71)	(-0.62)	(0.07)
N	713	711	708	702
adj-R^2	0.02	0.07	0.12	0.18

Table 6: Forecasts of the variance of excess returns on the stock market with the Federal funds rate: with and without output gap and inflation.

This table presents forecasting regressions of the form: $VAR_{t+1,t+h} = \alpha + \beta' X_t + \epsilon_{t+1,t+h}$, where $VAR_{t+1,t+h} = VAR_{t+1} + ... + VAR_{t+h}$ and VAR_t is the variance of daily returns on the CRSP value-weighted index in month t. In Panel A, X_t includes FF and $\log(D/P)$, the Fed funds rate and log dividend-price ratio on the CRSP value weighted stock index, respectively. In Panel B, X_t also includes GAP and $\pi_{t-12,t}$, the output gap of Cooper and Priestley (2009) and log-inflation over the 12 months ending in month t, respectively. The sample period is 1954:8-2013:12. t-statistics based on Hodrick (1992) standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Forecasts with FF and $\log(D/P)$				
	h=1	h=3	h=6	h=12
FF	0.00	0.00	0.01	0.04**
	(0.16)	(0.62)	(1.12)	(2.32)
$\log(D/P)$	-0.11***	-0.37***	-0.80***	-1.74***
	(-6.72)	(-6.95)	(-7.11)	(-7.02)
N	713	711	708	702
adj-R^2	0.04	0.06	0.09	0.15
Panel B: Forecasts with FF, $\log(D/P)$, GAP, and $\pi_{t-12,t}$				
	h=1	h=3	h=6	h=12
FF	-0.01	-0.02	-0.04	-0.04
	(-1.33)	(-1.41)	(-1.37)	(-0.81)
$\log(D/P)$	-0.16***	-0.52***	-1.05***	-2.04***
	(-7.33)	(-6.94)	(-7.14)	(-7.24)
GAP	-0.40***	-1.15***	-1.79***	-1.85*
	(-3.76)	(-3.45)	(-3.07)	(-1.74)
$\pi_{t-12,t}$	1.56***	5.60***	11.45***	17.00***
	(3.16)	(3.13)	(3.14)	(2.85)
N	713	711	708	702
adj-R^2	0.05	0.10	0.14	0.18

Table 7: Returns on FFED prior to and during the zero lower bound

This table presents two time series regressions of $FFED$ on the market excess return. In column (1), the sample period is the last 60 months before the FOMC instituted the zero lower bound (2004:1-2008:12). In column (2), the sample period is the last 60 months of the sample during which the federal funds rate is at the "zero lower bound" (2009:1-2013:12). Units are percent per month so that 0.01 denotes one basis point. Heteroskedasticity-robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)
MKT	0.133**	0.087
	(2.10)	(0.74)
α	0.515**	-0.004
	(2.53)	(-0.01)
N	60	60
adj-R^2	0.077	0.002

Table 8: GMM tests with $FFED$ and related factors

This table presents estimated discount factor coefficients and risk premiums from GMM estimations of the linear pricing kernel model with factors MKT, $FFED$, F_{FF}, F_{BILL}, F_{rr}, and F_{π}. The test assets are the monthly excess returns on the Fama French 25 portfolios formed on size and book-to-market and the 25 portfolios formed on size and momentum. Panel A and B present one-step and two-step GMM estimates, respectively. R^2_{OLS} denotes the R^2 from the OLS cross-sectional regression of average returns on βs defined in section 3, and $\overline{|\alpha|}$ denotes the mean absolute pricing errors expressed per annum. J denotes the Hansen (1982) J test statistic and p-values are next to the Js in parentheses. The sample is 1952:1-2013:12. Newey and West (1987) t-statistics based on three lags of serial correlation are in parentheses.

Panel A: (One-Step) MKT, $FFED$, F_{FF}, F_{BILL}, F_{rr}, F_{π}						
	MKT	$FFED$	F_{FF}	F_{BILL}	F_{rr}	F_{π}
b	-0.02	-0.20	-0.05	0.04	0.00	0.07
$t(b)$	(-0.97)	(-2.98)	(-0.36)	(0.35)	(-0.04)	(0.98)
λ	0.62	0.89	-0.72	-0.66	0.28	-0.30
t_{λ}	(2.60)	(4.24)	(-3.77)	(-3.00)	(1.85)	(-2.66)
R^2_{OLS} =0.88, $\overline{|\alpha|}$ =0.88						
Panel B: (Two-Step) MKT, $FFED$, F_{FF}, F_{BILL}, F_{rr}, F_{π}						
	MKT	$FFED$	F_{FF}	F_{BILL}	F_{rr}	F_{π}
b	-0.01	-0.19	0.09	-0.02	-0.02	0.02
$t(b)$	(-0.40)	(-5.67)	(0.89)	(-0.21)	(-0.57)	(0.33)
λ	0.94	0.98	-1.19	-1.18	0.40	-0.37
t_{λ}	(4.48)	(8.87)	(-8.56)	(-7.54)	(3.80)	(-5.05)
J =152.43(0.00)						

Table 9: GMM tests with $FFED$ and the intermediary leverage mimicking portfolio

This table presents estimated discount factor coefficients and risk premiums from GMM estimations of several linear pricing kernel models. The test assets are the monthly excess returns on the union of the Fama French 25 portfolios formed on size and book-to-market and the 25 portfolios formed on size and momentum. The first three columns present estimates from the model with factors MKT and LMP and the last four columns present estimates with $FFED$ as well. Panel A uses one-step GMM and Panel B uses two-step GMM. b and λ denote the discount factor coefficients and risk premiums, respectively, for each factor. R^2_{OLS} denotes the R^2 from the OLS cross-sectional regression of average returns on βs defined in section 3, and $|\alpha|$ denotes the mean absolute pricing errors expressed per annum. J denotes the Hansen (1982) J test statistic and p-values are next to the Js in parentheses. The sample is 1952:1-2013:12. Newey and West (1987) t-statistics based on three lags of serial correlation are in parentheses.

Panel A: (One-Step) MKT, LMP, $FFED$						
	MKT	LMP		MKT	$FFED$	LMP
b	0.00	-0.11	b	-0.01	-0.14	-0.04
$t(b)$	(-0.30)	(-4.78)	$t(b)$	(-0.78)	(-2.81)	(-1.07)
λ	0.64	1.21	λ	0.58	0.78	1.11
t_λ	(2.65)	(5.61)	t_λ	(2.24)	(4.70)	(4.64)
R^2_{OLS} =0.57, $\overline{\lvert\alpha\rvert}$ =1.78			R^2_{OLS} =0.85, $\overline{\lvert\alpha\rvert}$ =1.00			
Panel B: (Two-Step) MKT, LMP, $FFED$						
	MKT	LMP		MKT	$FFED$	LMP
b	0.01	-0.12	b	-0.01	-0.19	-0.05
$t(b)$	(0.61)	(-8.78)	$t(b)$	(-1.17)	(-7.2)	(-2.83)
λ	0.53	1.35	λ	0.68	1.03	1.45
t_λ	(2.92)	(9.18)	t_λ	(3.47)	(9.98)	(8.76)
J =235(0.00)			J =164(0.00)			

Internet Appendix to Monetary Policy Surprises, Investment Opportunities, and Asset Prices

December 14, 2015

This Internet Appendix includes supplemental results to augment those in the paper. Section 1 presents simulations to validate the construction of $FFED$. Section 2 presents asset pricing results with the monthly frequency measure of Federal funds policy shocks used by Bernanke and Kuttner (2005). Section 3 discusses a vector autoregression-based measure of Federal funds policy shocks. Section 4 presents estimated $\beta_{FFED}s$ for the 50 size and book-to-market and size and momentum portfolios to explain how $FFED$ prices these assets. Finally, section 5 presents a review of related literature.

1. Simulations

Here I present simulation evidence that picking a "lucky" combination of the base assets does not generate my main asset pricing results with $FFED$. I form ten thousand random "$FFED$"s by regressing i.i.d. normal noise onto the eight base assets that I used to make $FFED$ over the monthly sample period 1952:1-2013:12. I then simulate some of the important test statistics that I generate in this paper and consider the null hypothesis that my results are simply due to randomly picking a particularly powerful combination of the base assets.

More specifically, I generate (n=744) random sequences of i.i.d. standard normal random variables, denoted $z_{i,t}$, $i = 1, ..., 10,000$, $t = 1, ..., 744$. $t = 1$ through $t = 744$ corresponds to each month from January 1952 through December 2013. I then estimate the same regressions as for

$FFED$ for each i:

$$z_{i,t} = a_i + (szbm_{11}, szbm_{15}, szbm_{51}, szbm_{55}, szm_{11}, szm_{15}, szm_{51}, szm_{55})_t \cdot b_i + \epsilon_{it}, \tag{1}$$

I normalize the vector $\hat{b}_i$ to have length 1 so that the simulated value of the mimicking portfolio, $FFED_{it}^{SIM}$, in month t is given by:

$$FFED_{it}^{SIM} = (szbm_{11}, szbm_{15}, szbm_{51}, szbm_{55}, szm_{11}, szm_{15}, szm_{51}, szm_{55})_t \cdot \frac{\hat{b}_i}{\|\hat{b}_i\|}. \tag{2}$$

Note that the simulated $FFED_{it}^{SIM}$s keep the same one historical sample of $szbm_{11}$, $szbm_{15}$, $szbm_{51}$, $szbm_{55}$, szm_{11}, szm_{15}, szm_{51}, and szm_{55}, but I generate random noise to project onto this one history of base assets. Hence, the simulations address the likelihood of whether a randomly drawn "FFED" would produce as strong or stronger results as those reported in the paper, simply by choosing the right combination of the base assets by chance.

Figure A1 Panels A, B and C plot distributions of the estimated intercepts from the time-series regressions of SMB, HML and MOM on each of the 10,000 randomly generated $FFED_i^{SIM}$s. The observations between the red line correspond to intercepts that are as small, or smaller, in absolute value, to corresponding intercepts reported in Table 3. Beneath the x-axis are the empirical frequencies of observations bound between the red lines. Panel D presents a scatter plot with of the intercepts from the regressions of HML and MOM on each of the ten-thousand randomly generated "$FFED$"s. The red lines cross through pairs of intercepts with the same absolute values as those from the corresponding regression reported in Table 3 Panel B Right. The yellow dots correspond to pairs of intercepts where both intercepts are less-than or equal to those reported by Table 3. Beneath the x-axis is the empirical probability that one of the dots depicted is yellow. None of the ten-thousand randomly generated $FFED^{SIM}$s generates αs on HML and MOM in the estimation of (8) that are as small or smaller in absolute value as those reported in Table 3. In short, it is extremely unlikely that a random combination of the base assets would generate a factor that generates the same powerful time-series results as $FFED$.

Then, Figure A2 Panels A and B present histograms of mean absolute pricing errors $\overline{|\alpha|}$s and cross-sectional R^2_{OLS}s (defined in Section 3) for the GMM tests in table 4, for each of the ten-thousand simulated "$FFED$"s. The vertical red lines denote the corresponding quantity reported in Table 4. Beneath the x-axis in Panel A is the empirical probability that a random $FFED^{SIM}$ would have an $\overline{|\alpha|}$ that is less than or equal to that earned by the model $MKT, FFED$ in Table 4. Panel B reports a similar probability that a cross-sectional R^2_{OLS} on a randomly generated $FFED^{SIM}$ would be greater than or equal to that earned by the model $MKT, FFED$ in Table 4. Panel C presents a scatter of simulated cross-sectional R^2_{OLS}s and $\overline{|\alpha|}$s. The two red lines intersect at the corresponding $\overline{|\alpha|}$ and R^2_{OLS} reported in Table 4. Yellow dots denote combinations of $\overline{|\alpha|}$ and R^2_{OLS}s where $\overline{|\alpha|}$ is no greater and the R^2_{OLS} is no less than the corresponding numbers in Table 4. Beneath the x-axis in Panel (C) is the empirical probability that a dot is yellow.

Only 25 out of 10,000 randomly generated factors combine with the market excess return to yield both a mean absolute pricing error that is less than or equal to that reported in Table 4 and a cross-sectional R^2_{OLS} that is as large or larger than that reported in Table 4. For each simulated $FFED^{SIM}_i$, let $t_{i,SMB}$, $t_{i,HML}$ and $t_{i,MOM}$ and $t_{FFED^{SIM}_i}$ denote the t-statistics corresponding to the test that b_{SMB}, b_{HML}, b_{MOM} and $b_{FFED^{SIM}_i}$ are significantly different than 0 from the one-step GMM estimation of the factor model given by $f = (MKT, SMB, HML, MOM, FFED^{SIM}_i)$. This is analogous to the test in Panel E of Table 4. I perform the following two computations:

- 0.25 % of the 10,000 simulated $t_{i,SMB}$, $t_{i,HML}$, $t_{i,MOM}$ and $t_{FFED^{SIM}_i}$ fail to reject the null that b_{SMB}, b_{HML} and b_{MOM} are 0 at the 10% level while rejecting the null that $b_{FFED^{SIM}_i} = 0$ at the 5% level. That is, 0.25 % of the simulated $FFED^{SIM}_i$s satisfied:

$$|t_{i,SMB}| >= \Phi^{-1}(0.95),\ |t_{i,HML}| >= \Phi^{-1}(0.95),\ |t_{i,MOM}| >= \Phi^{-1}(0.95), \text{ and} \quad (3)$$
$$|t_{FFED^{SIM}_i}| < \Phi^{-1}(0.975),$$

  where Φ denotes the standard normal CDF.

- 0.13 % of the 10,000 simulated $t_{i,SMB}$, $t_{i,HML}$, $t_{i,MOM}$ were as small or smaller as those reported in Table 4 while $t_{FFED^{SIM}_i}$ was as large or larger. That is, 0.13 % of the simulated

$FFED_i^{SIM}$s satisfied:

$$|t_{i,SMB}| \leq 1.30,\ |t_{i,HML}| \leq 1.12,\ |t_{i,MOM}| \leq 1.32, \text{ and} \tag{4}$$
$$|t_{FFED_i^{SIM}}| >= 3.42.$$

Overall, the empirical probabilities from the simulations allow me to reject the null hypothesis, at the 1% level, that I would observe time-series or cross-sectional asset pricing results that are as strong as those of $FFED$, simply by randomly generating mimicking portfolios from the history of $szbm_{11}$, $szbm_{15}$, $szbm_{51}$, $szbm_{55}$, szm_{11}, szm_{15}, szm_{51}, and szm_{55}.

2. Supplemental tests with monthly Federal funds policy shocks

My study is motivated largely from the ICAPM implications of the evidence from Bernanke and Kuttner (2005) that the impacts of monetary policy on stock prices comes largely through news about expected returns. They do this using a monthly frequency proxy of Federal funds policy shocks in order to use a Campbell and Shiller (1988)-type decomposition. In particular, they do not use the more precisely measured daily policy shocks that my study takes advantage of. In this section I perform additional analysis to determine if the monthly frequency measure of Bernanke and Kuttner (2005) also commands a positive risk premium. This has at least two benefits. The first is to verify that my study is well-founded. A negative risk premium on the monthly Bernanke and Kuttner (2005) Federal funds policy shock measure would cast doubt on the ICAPM implication that I use to explain the positive risk premium on my Federal funds announcement surprise portfolio ($FFED$). The second benefit of testing the monthly Bernanke and Kuttner (2005) measure is that it is already regularly spaced and can be used in asset pricing tests directly without the use of a mimicking portfolio. This provides further evidence of the robustness of the positive risk premium on Federal funds policy shocks.

2.1. Construction and properties of the monthly measure

Letting D_m denote the number of calendar days in month m, the average daily Federal funds rate implied by the one-month ahead Federal funds futures contract on the last day of month $m-1$ is given by:

$$f^1_{m-1,D_{m-1}} = \$100 - P^1_{m-1,D_{m-1}}, \quad (5)$$

where $P^1_{m-1,D_{m-1}}$ denotes the settlement price of the one-month-ahead futures contract on the last day of month $m-1$. To get a sense of how well $f^1_{m-1,D_{m-1}}$ forecasts one-month-ahead Federal funds rates, Figure A3 presents a plot of three monthly-frequency time series. The first is the average daily Federal funds rate each month, $\overline{FF}_m$. The second is the average daily target Federal funds rate, $\overline{FFT}_m$. The third is the lagged one-month-ahead futures rate, $f^1_{m-1,D_{m-1}}$. The series nearly lay on top of each other with only a small amount of noise separating the average daily Federal funds rate from the other two series. In particular, the futures contracts appear to be an accurate predictor of any of the two ex-post rates in the plot, consistent with the now-outdated evidence of Krueger and Kuttner (1996) who find that $f_{m-1,D_{m-1}}$ yields a rational and efficient forecast of the Federal funds rate at the one-month and two-month horizon.

I formally test this forecasting power as follows. Following, Kuttner (2001), Bernanke and Kuttner (2005) and others, I define the "expected" change in the futures rate in month m to be the difference between the futures rate at the end of the previous month and the target rate at the end of the previous month: $f^1_{m-1,D_{m-1}} - FFT_{m-1}$. Then, I estimate forecasting regressions of the form:

$$\Delta X_m = a + b\left(f^1_{m-1,D_{m-1}} - FFT_{m-1}\right) + \epsilon_m, \quad (6)$$

where X_m denotes the average daily effective federal funds rate or target federal funds rate, in month m. Table A1 presents the results.

INSERT TABLE A1 ABOUT HERE

Table A1 also includes the F statistics for the hypothesis that $b = 1$. The F test fails to reject the hypothesis that $b = 1$ in all four specifications. This is equivalent to failing to reject the null of a time-varying forecast error. Further, the futures rate seems to over predict the changes in federal funds rate by a constant 5 or 6 base points per annum, which is small. Hence, at the one-month horizon Federal funds futures contracts predict changes in the Federal funds rate with a small, seemingly constant error.

Following Krueger and Kuttner (1996), Kuttner (2001), Bernanke and Kuttner (2005) and others, I define the month-m surprise change in the target Federal funds rate by:

$$\bar{\Delta} r_m^u = \frac{1}{D_m} \sum_{d \in m} FFT_d - f_{m-1,D_{m-1}}^1. \tag{7}$$

FFT_d denotes the target Federal funds rate on day d of month m. The measure is available from January 1989 through November 2008 when the Federal Reserve quit publishing a single target rate. Starting December 16, 2008 the Federal Reserve began publishing a target range of Federal funds rates. In December 2008, I replace the target Federal funds rate with the average daily effective Federal funds rate in equation (7) because the Federal Reserve ceased to publish a single Federal funds target rate mid-month. I do not continue to construct $\bar{\Delta} r^u$ with the effective rate after December 2008 because the FOMC kept the Federal funds rate close to 0, and adopted so-called unconventional monetary policy, which makes the Federal funds rate a questionable proxy for monetary policy. Following the literature, I construct $\bar{\Delta} r^u$ using the average daily target rate in month m as opposed to the average effective rate over month m. One reason for doing this is that the spread between the average daily effective Federal funds rate represents high frequency fluctuations in the demand for Federal funds that is hard to forecast and does not reflect monetary policy (see, e.g., Bernanke and Blinder (1992)). To get a sense of how much of the variation in the Federal funds rate comes from $\bar{\Delta} r^u$, note that the correlation between $\bar{\Delta} r^u$ and $\Delta \overline{FF}_t$ is 0.24.

2.2. Asset Pricing Tests with $\bar{\Delta} r^u$

To estimate a risk premium on $\bar{\Delta} r^u$, I sort stocks based on their estimated exposures to past Federal funds surprises. Each month, I estimate the following model:

$$r_{it} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \beta^{\$} \bar{\Delta} r_t^u + \epsilon_{it}, \tag{8}$$

over the previous 60 months, for each common stock i in CRSP with at least 36 months of returns. I then sort these stocks into 5 value-weighted quintiles excluding those stocks with share prices below \$5 following Asparouhova, Bessembinder and Kalcheva (2013). I denote the excess return on the i-th quintile in month t as FED_{it} and the top-minus-bottom-$\beta_{\bar{\Delta}r^u}$-quintile spread as $FED_{5-1,t}$. That is:

$$FED_{5-1,t} \triangleq FED_{5t} - FED_{1t} \tag{9}$$

The series begins 1994:1, 60 months after $\bar{\Delta}r^u$ becomes available and lasts through 2008:12 (n=180).

In Panels A through C of Table A2, I estimate several models of the form:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p' X_t + \epsilon_{pt}, \tag{10}$$

where $p = FED_i,\ i = 1, 2, 3, 4, 5$ or $p = 5 - 1$. Panel A presents average returns, Panel B presents CAPM estimations ($X_t = MKT_t$), and Panel C presents Fama-French 3-factor model estimations ($X_t = (MKT, SMB, HML)'$).

Insert Table A2 about here

Average returns increase monotonically from the lowest to highest quintile portfolio. The top-minus-bottom quintile difference is economically significant at 58 base points per month, or equivalently 6.96% per annum. Similarly, the αs with respect to the CAPM model also increase monotonically from the bottom to the top quintile. The CAPM α on FED_{5-1} is 61 base points per month (7.32% per annum). In Panel C, the three-factor αs increase monotonically from the bottom to top quintile portfolios, with the spread FED_{5-1} earning a Fama-French three factor α of 72 base points per month (8.64% per annum). The three-factor abnormal return is also significant at the 5% level. Furthermore, the loading on the market return is negative in Panels B and C as well, consistent with FED_{5-1} acting as a mimicking portfolio for Federal funds innovations which are negatively correlated with market returns.

Panel D of Table A2 presents post-ranking $\beta_{\bar{\Delta}r^u}$s and β_{FFED}s from the following model:

$$r_{pt}^e = \alpha + \beta_p MKT_t + \beta_{X,p} X_t + \epsilon_t,\ X = \bar{\Delta}r^u,\ FFED. \tag{11}$$

The post-ranking $\beta_{\bar{\Delta}r^u}$s increase monotonically from FED_2 to FED_4 though the point estimates are not precisely estimated and the top and bottom quintiles both have negative, though insignificant post-ranking $\beta_{\bar{\Delta}r^u}$s. The $\beta_{\bar{\Delta}r^u}$ of FED_{5-1} is -0.61% with an insignificant t-statistic of $t = -0.17$. This level of imprecision in post-ranking betas for risk factors is not uncommon in post-ranking samples this length (see e.g., Pástor and Stambaugh (2003) Table 7). Hence, this evidence does not serve to reject a risk-based explanation for the relationship between ranking $\beta_{\bar{\Delta}r^u}$ and returns, just makes it less convincing. It is interesting to note, however, that the post-ranking β_{FFED}s follow a similar pattern as those on $\bar{\Delta}r^u$, increasing monotonically from quintile 1 to 4 but falling to an insignificant level in quintile 5.

Overall, the evidence from Table A2 suggests that the monthly innovations in the Federal funds rate ($\bar{\Delta}r^u$) earns a positive risk premium. Further, this risk premium is not subsumed by several common portfolio based risk factors, MKT, SMB and HML. The positive risk premium is consistent with the $\bar{\Delta}r^u$ improving investment opportunities. Unfortunately, the weak spread in post-ranking $\Delta\bar{r}^u$ βs precludes strong conclusions about the economic importance of the $\Delta\bar{r}^u$ risk premium.

2.2.1. Discussion of $\bar{\Delta}r$

Unfortunately, the measure $\bar{\Delta}r^u$ also suffers from several conceptual drawbacks. First, the existence of the futures contracts limits the measure to the 1989 through 2008 time period. Second, $\bar{\Delta}r^u$ could reflect the endogenous response of the Fed to changes in the economy during month m, as opposed to shocks to monetary policy. As noted by Bernanke and Kuttner (2005), this endogeneity would tend to attenuate the measured sensitivity of returns to Federal funds surprises because the Fed would, if anything, lower rates in response to a decrease in stock prices or bad news about the economy. However, Bernanke and Kuttner also find that $\bar{\Delta}r^u_m$ is negatively correlated with returns on the market, which is hard to reconcile with any explanation other than the market negatively reacting to shocks in the stance of Federal funds policy.

A second problem is that the Federal funds futures rate only equals the expected future Federal funds rate if investors are risk neutral. Rather, the futures rate is driven by the so-called "risk-neutral" expected future Federal funds rate. That is:

$$f^1_{m-1,D_{m-1}} = E^Q_{m-1}[\bar{r}_m] = E_{m-1}[\bar{r}_m] + \lambda_{m-1}. \tag{12}$$

$\bar{r}_m$ denotes the average daily Federal funds rate in month m. $E^Q_{m-1}[\cdot]$ and $E_{m-1}[\cdot]$ denote risk neutral and physical expectations, respectively. The risk-neutral expectation differs from the physical expectation by a risk premium λ_{m-1}. The risk premium may also be specific to futures contracts. In a form of market segmentation modeled early on by Hirshleifer (1988), returns on futures contracts reflect "hedging pressure" in which asymmetric hedging demand skews futures prices. In the context of Federal funds futures, Piazzesi and Swanson (2008) argue that banks create a tremendous hedging demand for protection against increases in Federal funds rates, driving down $\bar{\Delta}r^u$.

Finally, $\bar{\Delta}r^u_s$ also suffers from a time-aggregation issue due to the fact that Federal funds futures make a payment based on the average daily Federal funds rate. The construction of $\bar{\Delta}r^u$ will give less weight to equally informative policy news that comes out later in the month because fewer days worth of Federal funds rates will reflect the news. Without making assumptions about when relevant news comes out in a given month, this time aggregation issue does not have a simple fix. In spite of the attenuation from this source of noise, empirical results that use $\bar{\Delta}r^u$ are still strong. As such, Kuttner (2001) and Bernanke and Kuttner (2005), among others, simply accept this limitation in their analyses.

3. Vector autoregression-based innovations

The Monetary Policy literatures relies heavily on structural vector autoregressions (VARs) to identify regular time series of monetary policy shocks from the Federal funds Rate. (see e.g., Christiano, Eichenbaum and Evans (2005), or Christiano, Eichenbaum and Evans (1999) for a survey). Unfortunately, different VAR structural identification schemes tend to result in qualitatively different results, at least with the response of output and inflation to Federal funds shocks (see e.g., Uhlig (2005)).

Thorbecke (1997) uses this identified-VAR approach to construct monthly Federal funds policy shocks and estimates a negative risk premium on them. These Federal funds policy shocks are only orthogonalized ex post, and only with respect to industrial production and monthly inflation, which are themselves proxies for the business cycle and current and expected inflation. This orthogonalization can not perfectly isolate Federal funds policy shocks in real time given the richer information set that the market has in addition to just one measure of industrial production and inflation. It is therefore likely that the VAR-based Federal funds shocks still contain business cycle and inflation news that affects how these shocks impact asset prices. Hence, I replicate the policy shocks of Thorbecke (1997) and consider them in an ICAPM-type model with and without business cycle and inflation shocks. This allows me to test whether the risk premium on the Federal funds shocks are really driven by shocks to the business cycle and inflation as opposed to monetary policy shocks, consistent with my argument in Section 4 of the main body of the paper.

Following Thorbecke (1997), I estimate Federal funds policy shocks, denoted $\epsilon^{\perp}_{FF}$, as the orthogonalized innovations in the Federal funds rate from a 6-lag VAR. The recursive causal ordering used to identify the $\epsilon^{\perp}_{FF}$ is given by the order in which I list the variables in the VAR, which are:

1. Log industrial production growth (IP)
2. Log year-over-year inflation ($\pi_{t-12,t}$)
3. Log producers price index (PPI)
4. The Federal funds rate (FF)
5. Log non-borrowed reserves (NBR)
6. Log total reserves (TR)

The macro variables all come from the Federal Reserve website.

To test whether $\epsilon^{\perp}_{FF}$ still captures exposure to the business cycle and inflation, I estimate two ICAPM-type models, one with MKT and $\epsilon^{\perp}_{FF}$, and one that also adds the business cycle and inflation innovations $\epsilon^{\perp}_{IP}$, $\epsilon^{\perp}_{PPI}$, and $\epsilon^{\perp}_{\pi}$. I use similar test assets as Thorbecke (1997), the union of the ten CRSP size-decile portfolios and the Fama-French 17 industry portfolios.[1] I present estimates with two-step GMM as no coefficients are significant with one-step GMM. These estimates are in Table A3.

[1]Thorbecke (1997) formed 20 industry portfolios to pair with 10 size portfolios.

Insert Table A3 about here

$\epsilon_{FF}^{\perp}$ commands a negative risk premium. However, this risk premium becomes insignificant after adding the business cycle innovation $\epsilon_{IP}^{\perp}$, which earns a significant negative risk premium. This is consistent with the $\epsilon_{FF}^{\perp}$ earning a negative risk premium because it captures changes in the business cycle that the Fed responds to, in spite of the in sample orthogonalization.

4. Economic significance of λ_{FFED} and robustness

To determine the spread in returns accounted for by exposure to $FFED$, I estimate the β_{FFED} for each of the 50 portfolios via the model:

$$r_{pt}^{e} = \alpha_p + \beta_{p,MKT} MKT_t + \beta_{p,FFED} FFED_t + \epsilon_{pt}. \tag{13}$$

Table A4 presents the estimates. The spread between the average β_{FFED} of top book-to-market-quintile portfolios ($szbm_{15}$ through $szbm_{55}$) and the bottom book-to-market-quintile portfolios ($szbm_{11}$ through $szbm_{51}$) is 0.556. The risk premium on $FFED$ from Table 4 panel B is 0.81. This corresponds to a contribution of $0.556 * 0.81 * 12 = 6.05\%$ per annum in a spread in average returns between the extreme growth and value portfolios. Similarly, the spread in average β_{FFED}s between the smallest size-quintile portfolios and the largest size-quintile portfolios is 0.433. This contributes to the average portfolio in the smallest quintile earning $0.433 * 0.81 * 12 = 4.21\%$ per annum in average returns higher than the average top quintile portfolio.

Insert Table A4 about here

Finally, the average top momentum-quintile portfolio β_{FFED} is 0.586 and the average bottom momentum quintile portfolio β_{FFED} is -0.674, a spread of 1.26. This corresponds to a relatively large spread in returns of $1.26 * 0.81 * 12 = 12.25\%$ per annum between the average top and bottom momentum-quintile portfolios. Overall, the risk premiums earned by $FFED$ seem economically significant and accounting for exposure to $FFED$ accounts for a good deal of spread in returns related to size, value and momentum.

5. Related literature

Several recent studies consider the impact of monetary policy shocks on the risk premia of bonds. Hanson and Stein (2015) and Gertler and Karadi (2015) find that news of tighter monetary policy increases term premia and credit spreads, respectively. This evidence is analogous to that of Bernanke and Kuttner (2005) in the sense that they all suggest that tighter monetary policy raises aggregate expected excess returns. My evidence is consistent with the cross-sectional ICAPM implication of all three studies and extends them by showing how risk associated with monetary policy shocks helps to explain anomalies in the cross-section of stock returns.

The literature on monetary policy and stock returns has focused primarily on the time-series of returns whereas my paper contributes to the empirical evidence of monetary policy and the cross-section of stock returns. Early cross-sectional evidence comes from Thorbecke (1997) who isolates innovations in Federal funds rate using a vector auto-regression following Christiano, Eichenbaum and Evans (1996). Thorbecke focuses on the time-series effects of monetary policy shocks on broad stock market indices but also estimates an arbitrage pricing theory factor model with Federal funds innovations and other macroeconomic factors. Thorbecke estimates a negative risk premium for Federal funds innovations over the sample period 1967-1990. As shown above, I replicate Thorbecke's Federal funds innovations and estimate an ICAPM model with the market excess return, the Federal funds innovations and business cycle and inflation innovations. Consistent with my time-series results, I find that the Federal funds innovations risk premium is insignificant controlling for innovations in inflation and the business cycle. In particular, the VAR-based identification of Thorbecke (1997) seems to not capture Federal funds policy shocks.

More recently, Maio and Santa-Clara (2015) estimate a 3-factor model that includes the first difference in the federal funds rate and a market factor whose beta varies linearly with the lagged federal funds rate. Using portfolios sorted on book-to-market, long-term-reversal, asset growth, investment-to-assets and market value as test assets, they estimate a negative risk premium on the federal funds factor. Based on my results, the first-difference of the Federal funds rate would earn a negative risk premium because it primarily captures negatively priced innovations in the business cycle and inflation expectiations that the Fed responds to. Lioui and Maio (2014) also consider a measure that is very similar to the first difference in the Federal funds rate and find that it commands a negative risk premium in the stock portfolios formed on size and book-to-market along with the portfolios formed on size and long-term reversal. Their measure involves log-differencing a scaled federal funds rate as opposed to the simple first-difference used by Maio and Santa-Clara (2015). However, the two measures captures similar business cycle and inflation effects that carry a negative risk premium.

Relative to the cross-section, more evidence exists pertaining to the time-series relationship between innovations in Federal funds policy and asset prices. Jensen, Mercer and Johnson (1996) find that the stance of monetary policy impacts the average stock market returns and the degree of stock-market predictability with common forecasters such as the log dividend yield and default and term spreads. A large event study literature generally finds the positive Federal funds policy shocks lowers stock and bond prices (see, e.g., Kuttner (2001), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Bjørnland and Leitemo (2009)). Further event studies include Chen (2007) who finds that the reaction of the stock market to federal funds shocks varies over the business cycle and Ammer, Vega and Wongswan (2010) finds that the the impacts of monetary policy announcements on stock prices vary by industry, with more cyclical industries experiencing greater impacts of Federal funds shocks. Related, Boyd, Hu and Jagannathan (2005) posit that the reaction of stocks to unemployment news varies over the business cycle because in good times lower unemployment increases expected futures interest rates, likely due to the Federal reserve reaction, lowering stock prices.

Kuttner (2001) and Bernanke and Kuttner (2005) find that stock and bond prices both respond negatively to monthly-frequency futures based proxies of Federal funds policy shocks. Using a Campbell and Shiller (1988)-type cash flow - discount rate news decomposition following Campbell and Ammer (1993), Bernanke and Kuttner (2005) attributes most of the impact of monetary policy on stocks to a positive relationship between Federal funds surprises and the equity risk premium. Unfortunately, the results of Bernanke and Kuttner (2005) have at least two large concerns. The first is that the cash-flow discount rate decomposition relies on the monthly measure of Federal funds policy shocks, which means it is contaminated with business cycle and inflation changes that the Fed responds to. Second, VAR-based decompositions are extremely unreliable (see, e.g., Chen and Zhao (2009)). Using a mimicking portfolio allows me to capture the precision of the futures-based FOMC announcement shocks and then use the sign of the risk premium on the mimciking portfolio to makes similar inferences as the Campbell and Shiller (1988) decomposition.

Buraschi, Carnelli and Whelan (2014) also form a monthly frequency measure of monetary policy shocks. They focus on shocks to the expected future path of monetary policy based on a combination of survey data and a Taylor (1993) rule. They find these shocks have a strong impact on the expected returns on treasury bonds. They also find that among the Fama French 100 size & book-to-market portfolios, the ten portfolios with the highest sensitivities to these path shocks earn higher average returns than the ten portfolios with the lowest sensitivities to these path shocks. This is an interesting contrast to my results as their path-shock proxy negatively correlates with my measures of Federal funds policy shocks, yet still commands a positive risk premium.

The negative risk premium earned by most monthly-frequency Federal funds innovations is related to the results of Brennan, Wang and Xia (2004) and Petkova (2006) who estimate a negative risk premium on short-term real and nominal bill rates, respectively. Ang and Bekaert (2007) and Campbell (1996) find that these short-term interest rates negatively forecast returns so innovations in short-term interest rates should command a negative risk premium, similar to the Federal funds rate.

Most recent studies focus on the Federal funds rate as a proxy for monetary policy. However, some studies consider the related asset-pricing effects of money. Balvers and Huang (2009) find that a Consumption CAPM with real money growth, measured by growth in price-deflated M2, helps to explain the value premium. Furthermore, they estimate a positive risk premium on money growth. Chan, Foresi and Lang (1996) consider the inside money portion of M2 and M3 growth as risk factors. They also estimate a positive risk premium on money growth, which is analogous to a negative risk premium on the Federal funds rate. In enforcing its Federal funds rate target via open market operations, the Federal Reserve controls the monetary base. However, the money supply, generally measured by M2 or M3, depends not only on the monetary base, but also aggregate demand for money, which covaries strongly with the business cycle and inflation. Thus, these studies capture different effects than I do as I study shocks to monetary policy as opposed to the business cycle and inflation.

This paper also adds novel results to a growing literature on the noteworthy behavior of equity prices around FOMC announcements. Savor and Wilson (2014), for example, find that the unconditional CAPM prices a number of test assets well on days of macroeconomic announcements including FOMC announcements, but not on other days. My results are distinct from theirs in at least two ways. First, their CAPM results do not explain momentum returns, even on important announcement days. In contrast, my two-factor model does explain such returns. Second, my asset pricing results do not hold only on announcement days. Rather, my results are consistent with (i) investment opportunity set risk explaining value and momentum returns, and (ii) Federal funds annoucements being an important source of news about investment opportunities. Lucca and Moench (2015) document that since 1994 over 80% of the equity premium is earned in the 24 hours prior to scheduled FOMC meeting announcements. However, they find these pre-FOMC returns do not correlate with the Federal funds surprises that I use and conclude this phenomenon is presumably distinct from the exposure of stocks to policy announcements, which I study. Cieslak, Morse and Vissing-Jorgensen (2014) find that since 1994, the entire equity risk premium is earned in weeks 0, 2, 4, and 6 relative to FOMC meetings.[2] They argue that this likely reflects a risk premium associated with information coming from the Federal Reserve, though it is not explained by the content of FOMC announcements, the shocks from which are the focus of this paper.

My paper is also related to a growing literature on financial intermediaries and asset prices. In the models of Drechsler, Savov and Schnabl (2014) and He and Krishnamurthy (2013), a reduction in the Federal funds rate can lower borrowing costs for relatively risk-tolerant financial intermediaries. This in turn allows intermediaries to bid up asset prices, lowering risk premia and Sharpe ratios. Adrian, Etula and Muir (2014) construct a mimicking portfolio, LMP, for intermediary leverage, arguing that intermediary leverage summarizes the pricing kernel of intermediaries. Given that monetary policy affects asset prices at least in part through intermediaries, I investigate whether intermediary leverage explains the returns on $FFED$. In a three factor model with MKT, LMP

[2]The FOMC meets about every 6 weeks. Week 0 starts the day before an FOMC meeting.

and $FFED$, all three factors significantly help to price assets. Hence, intermediary leverage alone does not seem to fully explain the effects of monetary policy shocks.

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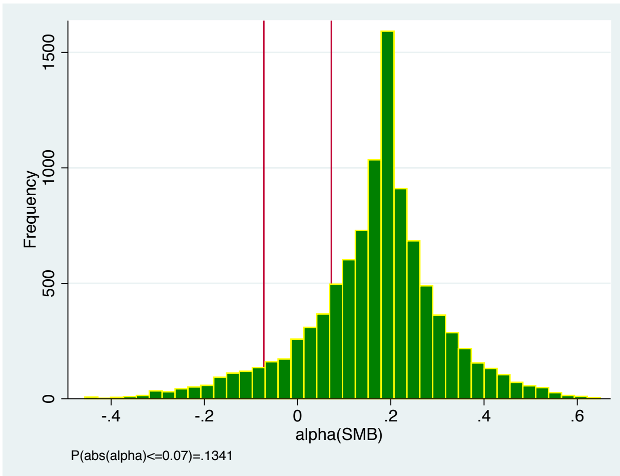
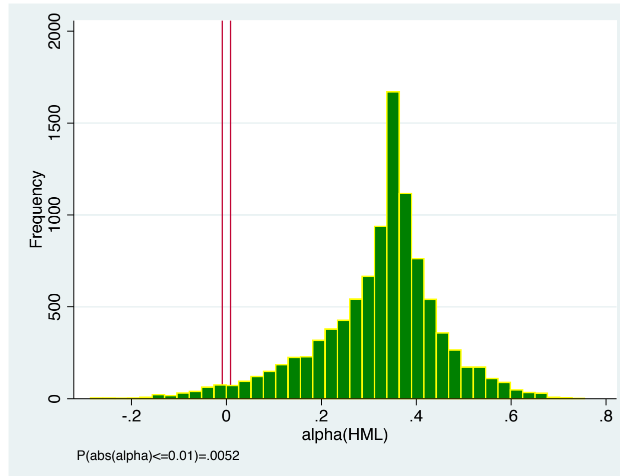
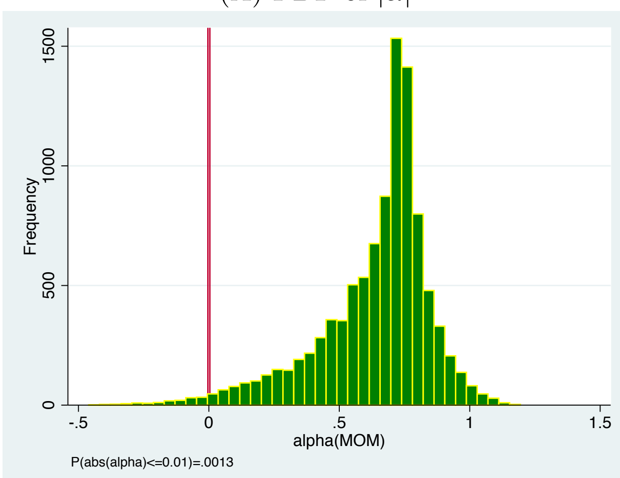
Appendix Figures



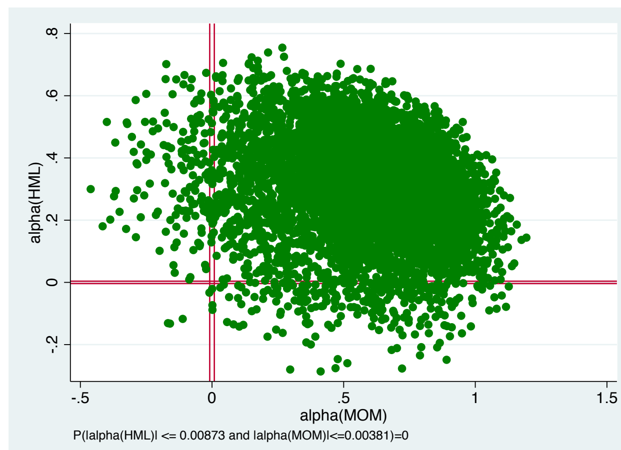
(A) PDF of $\overline{|\alpha|}$



(B) PDF of R^2_{OLS}

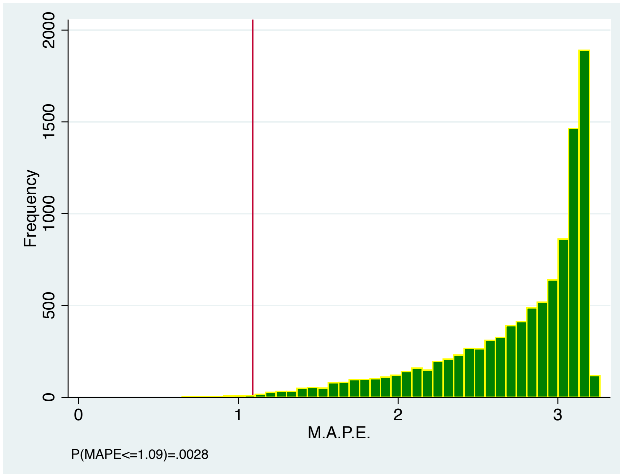


(C) Scatter of simulated $\overline{|\alpha|}$s and R^2_{OLS}s

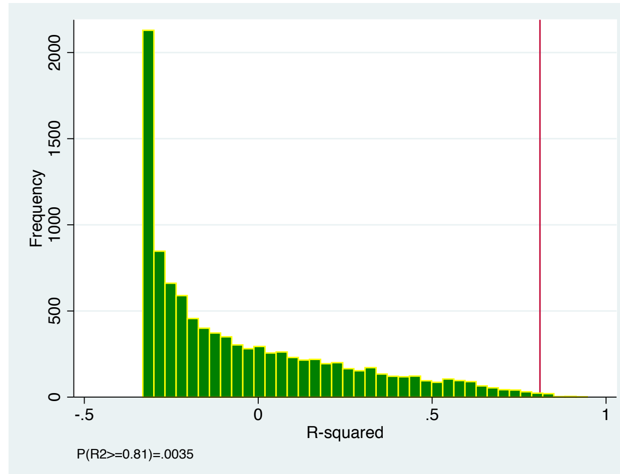


(D) Scatter of simulated $\overline{|\alpha|}$s and R^2_{OLS}s

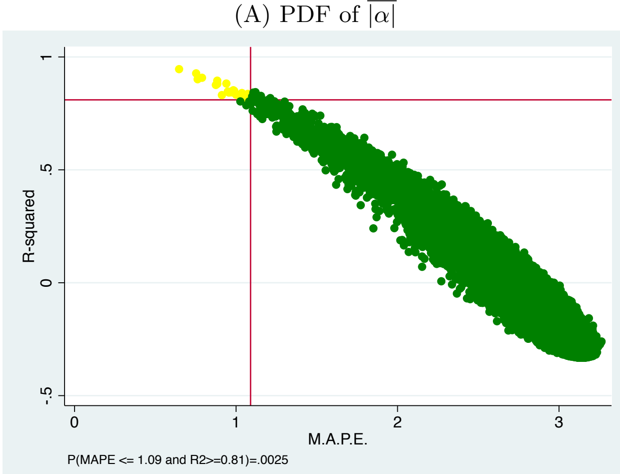
Figure A1: Intercepts from regressions of SMB, HML and MOM on simulated "FFED"s.
Panels A, B and C plot distributions of the estimated intercepts from the time-series regressions of SMB, HML and MOM on each of the 10,000 randomly generated $FFED_i^{SIM}$s. The observations between the vertical red lines correspond to intercepts that are as small, or smaller, in absolute value, to corresponding intercepts reported in Table 3. Beneath the x-axis are the empirical frequencies of observations between the red lines. Panel D presents a scatter plot with of the intercepts from the regressions of HML and MOM on each of the ten-thousand randomly generated "$FFED$"s. The yellow dots correspond to pairs of intercepts where both intercepts are less-than or equal to those reported by Table 3. Beneath the x-axis is the empirical probability that one of the dots depicted is yellow.



(A) PDF of $\overline{|\alpha|}$



(B) PDF of R^2_{OLS}



(C) Scatter of simulated $\overline{|\alpha|}$s and R^2_{OLS}s

Figure A2: Cross-sectional R^2_{OLS}s and mean absolute pricing errors for two-factor models with MKT and the simulated "FFED"s.

Panels A and B present histograms of mean absolute pricing errors $\overline{|\alpha|}$s and cross-sectional R^2_{OLS}s (defined in section 3) for the GMM tests in table 4, for each of the ten-thousand simulated "$FFED$"s. The vertical red lines denote the corresponding quantity reported in Table 4. Beneath the x-axis in Panel A is the empirical probability that a random $FFED^{SIM}$ would have an $\overline{|\alpha|}$ that is less than or equal to that earned by the model $MKT, FFED$ in Table 4. Panel B has a similar probability that a cross-sectional R^2_{OLS} on a randomly generated $FFED^{SIM}$ would be greater than or equal to that earned by the model $MKT, FFED$ in Table 4. Panel C presents a scatter of simulated cross-sectional R^2_{OLS}s and $\overline{|\alpha|}$s. The two red lines intersect at the corresponding $\overline{|\alpha|}$ and R^2_{OLS} reported in Table 4. Yellow dots denote combinations of $\overline{|\alpha|}$ and R^2_{OLS}s where $\overline{|\alpha|}$ is no greater and the R^2_{OLS} is no less than the corresponding numbers in table 4. Beneath the x-axis in Panel (C) is the empirical probability that a dot is yellow.

Figure A3: This figure depicts three monthly time series. The first two are the monthly averages of the effective (blue) and target (red) federal funds rates, respectively. The third time series is the futures rate from the one-month ahead futures contract at the end of the previous month (green). This series is the futures-based "expected" average daily federal funds rate for the current month. The futures rate series spans 1989:1-2008:12 December 2008 and the other three series span 1982:9-2008:12. Units are % per annum.

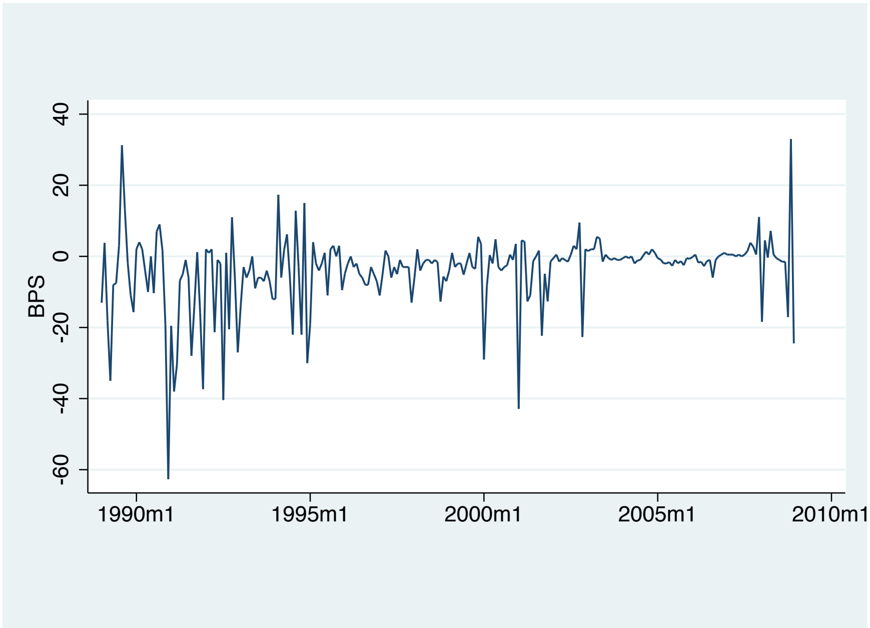


Figure A4: This figure depicts the monthly-frequency measure of federal funds surprises $\bar{\Delta} r_t^u$. The sample is 1989:1-2008:12. Units are basis points per annum.

Table A1: Forecasts of Monthly Changes in Fed Funds Rates with Expected Changes from Futures Contracts

This table presents estimates of one-month ahead futures forecasting regressions of the form: $\Delta X_m = a + b\left(f^1_{m-1,D_{m-1}} - FFT_{m-1}\right) + \epsilon_m$. $f^1_{m-1,D_{m-1}}$ denotes the one-month ahead futures rate on the last day of month $m-1$ and FFT_{m-1} denotes the target federal funds rate on the last day of month $m-1$. In columns 1 and 2, X_m denotes the average daily effective federal funds rate and target federal funds rate, respectively, in month m. Units are APR's so that 0.01 denotes one basis point per annum. F denotes the F statistic from a Wald test of the hypothesis that $b = 1$ for each regression and p_F is the corresponding p-value. The sample is 1989:1-2008:12. Heteroskedasticity-robust t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

	$\Delta\overline{FF}_m$	$\Delta\overline{FFT}_m$
b	0.98***	0.95***
	(7.45)	(6.40)
a	-0.05***	-0.05***
	(-4.64)	(-4.27)
R^2	0.32	0.33
F	0.02	0.10
p_F	0.88	0.75

Table A2: Quintile portfolios sorted on exposure to $\bar{\Delta}r^u$

Each month, I sort common stocks in CRSP into five value-weighted quintiles based on their estimate β^r from the following regression estimated over the previous 60 months: $r_{it} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \beta^r \Delta\tilde{r}_t^u + \epsilon_{it}$. Panels A, B and C report average returns, CAPM estimates, and Fama French three factor model estimates, respectively, for each of the quintile portfolios and the top-minus-bottom quintile portfolio FED_{5-1}. In each panel, column (i) presents estimates for quintile (i) with column $(5-1)$ presenting estimates for FED_{5-1}. Panel D presents post-ranking betas of each portfolio from the following regressions: $r_{pt}^e = \alpha + \beta_p MKT_t + \beta_{X,p} X_t + \epsilon_t$, where $X = \Delta r_t^u$, or $FFED$ and r_{pt}^e denotes the excess return on portfolio p. The post-ranking sample is 1994:1-2008:12 (n=180). t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(5 - 1)
Panel A: Average Returns						
Avg	0.06	0.29	0.34	0.46	0.64	0.58**
	(0.13)	(0.87)	(1.12)	(1.49)	(1.50)	(2.07)
Panel B: CAPM Factors Estimation						
α	-0.33*	0.00	0.08	0.19*	0.29	0.61**
	(-1.78)	(0.01)	(0.69)	(1.88)	(1.52)	(2.19)
MKT	1.27***	0.94***	0.83***	0.88***	1.16***	-0.11*
	(30.71)	(36.69)	(31.20)	(38.25)	(27.41)	(-1.69)
N	180	180	180	180	180	180
adj. R^2	0.840	0.883	0.845	0.891	0.807	0.010
Panel C: Fama French 3 Factors Estimation						
α	-0.39**	-0.02	0.00	0.17*	0.33*	0.72**
	(-2.22)	(-0.19)	(0.02)	(1.87)	(1.76)	(2.57)
MKT	1.26***	1.00***	0.93***	0.93***	1.10***	-0.16**
	(28.84)	(40.07)	(39.38)	(40.63)	(23.97)	(-2.24)
SMB	0.24***	-0.16***	-0.13***	-0.13***	0.10*	-0.14*
	(4.61)	(-5.57)	(-4.64)	(-4.94)	(1.75)	(-1.74)
HML	0.10	0.09**	0.22***	0.08**	-0.12*	-0.22**
	(1.55)	(2.42)	(6.47)	(2.35)	(-1.81)	(-2.18)
N	180	180	180	180	180	180
adj. R^2	0.856	0.911	0.902	0.913	0.817	0.030
Panel D: Post-ranking βs						
$\beta_{\bar{\Delta}r^u}$	-0.59	-1.61	1.93	2.98**	-1.20	-0.61
	(-0.25)	(-1.10)	(1.27)	(2.30)	(-0.49)	(-0.17)
$FFED$	-20.67***	-11.70***	1.81	12.06***	-0.18	20.50*
	(-2.95)	(-2.67)	(0.39)	(3.10)	(-0.02)	(1.89)

Table A3: GMM with Thorbecke (1997) Fed funds innovations

This table presents estimates from two-step GMM estimations of two linear pricing kernel models. The test assets are the monthly excess returns on Fama-French 17 industry portfolios and the 10 CRSP size portfolios. The first three columns present estimates with factors MKT, and $\epsilon_{FF}^{\perp}$, and the last three columns present estimates with factors MKT, $\epsilon_{FF}^{\perp}$, $\epsilon_{IP}^{\perp}$, $\epsilon_{PPI}^{\perp}$, and $\epsilon_{\pi}^{\perp}$. b and λ denote the discount factor coefficients and risk premiums, respectively, for each factor. J denotes the Hansen (1982) J test statistic and p-values are next to the Js in parentheses. The sample is 1967:1-1990:12. Newey and West (1987) t-statistics based on three lags of serial correlation are in parentheses.

	MKT	$\epsilon_{FF}^{\perp}$		MKT	$\epsilon_{FF}^{\perp}$	$\epsilon_{IP}^{\perp}$	$F_{\pi}^{\perp}$	$F_{PPI}^{\perp}$
b	0.01	0.01	b	0.03	0.01	0.01	0.00	0.00
$t(b)$	(0.63)	(2.27)	$t(b)$	(1.06)	(1.29)	(2.83)	(0.30)	(-0.63)
λ	0.27	-59.55	λ	-0.07	-47.88	-116.65	-7.09	18.66
t_{λ}	(0.80)	(-2.29)	t_{λ}	(-0.15)	(-1.26)	(-2.83)	(-0.22)	(0.62)
J =59(0.00)			J =26(0.25)					

Table A4: $FFED$ Beta Estimates for the 25 Size and Book-to-Market Sorted Portfolios and 25 Size and Momentum Sorted Portfolios: January 1952 to December 2013

This table presents estimates of β_{FFED} and the corresponding t-statistics from the model $r^e_{pt} = \alpha_p + \beta_{p,MKT} MKT_t + \beta_{p,FFED} FFED_t + \epsilon_{pt}$. Panel A presents the estimates for the 25 size and book-to-market portfolios. Panel B presents the estimates for the 25 size and momentum portfolios.

Panel A: β_{FFED} for 25 Size and Book-to-Market Portfolios

	Book-to-Market					Book-to-Market				
Size	Low	2	3	4	High	Low	2	3	4	High
	β_{FFED}					$t(\beta_{FFED})$				
Small	0.05	0.33	0.48	0.60	0.85	0.55	4.65	8.32	11.17	15.12
2	-0.02	0.28	0.44	0.54	0.70	-0.26	5.66	10.06	12.58	13.43
3	-0.05	0.22	0.33	0.45	0.57	-0.94	5.61	8.99	11.61	11.67
4	-0.09	0.12	0.23	0.37	0.44	-2.31	3.78	6.46	9.77	8.79
Big	-0.22	0.02	0.01	0.19	0.22	-8.51	0.78	0.39	4.64	4.06

Panel B: β_{FFED} for 25 Size and Momentum Portfolios

	Momentum					Momentum				
	Low	2	3	4	High	Low	2	3	4	High
	β_{FFED}					$t(\beta_{FFED})$				
Small	-0.53	0.23	0.44	0.57	0.64	-6.07	3.82	8.38	11.20	9.91
2	-0.53	0.08	0.35	0.50	0.65	-7.17	1.42	8.03	12.22	11.88
3	-0.64	-0.03	0.19	0.44	0.61	-9.51	-0.74	4.80	12.92	12.55
4	-0.77	-0.19	0.07	0.30	0.61	-11.88	-4.44	2.21	10.54	13.95
Big	-0.90	-0.39	-0.11	0.16	0.42	-15.65	-9.68	-3.70	5.47	10.22