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Factor returns and FOMC announcements: The role of sentiment

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ABSTRACT

We examine the dynamics of long-short factor returns on FOMC announcement days and the role of sentiment. We find that factor returns are negative on FOMC announcement days. Moreover, on these days returns are significantly lower following low sentiment periods. Hence, investor sentiment is a key driver of factor returns on FOMC days and this effect emanates mainly from the short portfolio leg of each factor.

1. Introduction

Factor risk premiums such as size, value, momentum and low volatility are significant drivers of returns over time, across assets and geographies.[3] A fundamental research question in the empirical asset pricing literature is whether factor premiums constitute rational compensation for risk or inefficiencies caused by investors' behavioral biases. To better understand the driving forces of factor premiums, this paper examines the impact of market sentiment on factor returns during days of Federal Open Market Committee (FOMC) announcements. Our results show that the state of investor sentiment is a significant driver of time-variation in factor returns on FOMC announcement days and sentiment mainly affects the returns of the short leg of factor portfolios.

The FOMC announcement days are useful events to study the effect of sentiment on stock prices because important information regarding monetary policy and the path of the economy is conveyed to market participants. We look at factor returns constructed from long-short strategies that capture well-known equity risk premiums such as size, value, momentum and low volatility.[4] Why do factor returns on FOMC days vary with market sentiment? Since factor portfolios are constructed using a long portfolio leg that consists of relatively "underpriced" stocks and a short portfolio leg that consists of relatively "overpriced" stocks, stock mispricing in the cross section may be driven by market wide sentiment. Following Stambaugh, Yu, and Yuan (2012) we test whether overpricing is more prevalent than underpricing since shorting a stock is more difficult than buying a stock. We expect sentiment to exert a higher influence on the short leg of factor portfolios.

In the empirical analysis we find that factor returns on FOMC announcement days are significantly lower following low sentiment periods. The variation of factor returns stems mainly from the variation of returns in short portfolio legs. Both long and short portfolio legs tend to have positive returns on FOMC announcement days. However, because low sentiment tends to exert a higher positive effect on the short portfolio leg that consists of relatively "overpriced" stocks the long-short spread becomes negative. We find that the FOMC effect is most pronounced in the case of factor portfolios that capture the low beta/volatility anomaly. This is because the short leg in low beta/volatility portfolios consists of high beta stocks with significant exposure to market wide sentiment. When we exclude daily returns that occur on FOMC days following low sentiment

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[3] The discovery of factor premiums in academic studies has had a profound impact on the investment management industry. Portfolio strategies that capture factor premiums are known as "smart" beta strategies. As of June 2017, there were about 1,320 of smart beta products with approximately 707 billion in assets under management, indicating an annual growth rate of 18% and 29%, respectively (Morningstar, 2017). Ang (2014) provides a comprehensive description of factor investing.

[4] We focus on these factors because size, value, momentum and low vol are the most popular factor premia in the investment industry and can be actively traded through "smart beta" ETFs. The academic finance and accounting literature documents hundreds of stock market anomalies that explain asset returns, dubbed by Cochrane (2011) as "a zoo of new factors". As a robustness check, we also employ the returns of 185 market anomalies (Hou, Xue, & Zhang, 2020).

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levels the improvement is economically significant, especially in low beta/volatility factor portfolios, with an increase in Sharpe ratios that ranges between 7 % to 100 %.

Our empirical results are robust along several dimensions, including extending the number of factors to 185 different long-short factor portfolios, controlling for systematic risk and different types of macro announcement news.

By looking at factor returns, our study is related to different strands of the literature. Several studies look at the response of stock prices to scheduled macroeconomic and monetary announcements. Savor and Wilson (2013) find that stock market returns tend to be 0.1 % higher on days when news about inflation, unemployment, or interest rates is announced. Lucca and Moench (2015) examine returns ahead of scheduled announcements and document large excess returns of about 0.5 % on the S&P 500 index during the 24 h leading to FOMC announcements.[5] We contribute to this literature by looking at the dynamics of the factor returns on FOMC announcement days, rather than just the market excess return.

Although classical finance theory leaves no role for investor sentiment, Baker and Wurgler (2006) present evidence that investor sentiment, defined as a belief about future cashflows and risks that is not justified by fundamentals, significantly affects the cross-section of stock return. Stambaugh et al. (2012) use Baker and Wurgler's (2006) sentiment index to explore the role of investor sentiment for a broad set of anomalies in cross-sectional stock returns. They show that long-short strategies are more profitable following high levels of sentiment. We extend Stambaugh et al. analysis from monthly to daily frequency and focus on FOMC announcement days. Our results suggest that factor returns on FOMC announcement days are time varying and significantly lower following low sentiment periods.

Numerous papers analyze factor performance over calendar time, such as monthly or day-of-the-week effects. For instance, Birru (2018) defines speculative stocks as those that are difficult to arbitrage or to value and finds that factors for which the speculative leg is the short (long) leg experience the highest (lowest) returns on Monday. We document that the response of factor returns may be state-dependent, rather than time-dependent.

In a recent study, Engelberg, Mclean, and Pontiff (2018) test the return response of about 97 different long-short portfolios designed to capture well know stock market anomalies. They find that anomaly returns are significantly higher on days of firm-specific information news like corporate news days and earning announcement days. Our results are complementary to those of Engelberg et al. (2018) by looking at monetary and macroeconomic, rather than corporate, news. In addition, our findings suggest that the excess returns are mostly concentrated on the short leg, instead of coming from both the long and short leg portfolios.

2. Data: fed announcements, factor portfolios and investor sentiment

2.1. Fed announcements

The FOMC is the monetary policy body of the US Federal Reserve System. It holds eight regularly scheduled meetings each year, approximately one meeting every six weeks. The dates of scheduled FOMC meetings are set far in advance, and thus their occurrence can be viewed as widely known to investors ahead of time. In contrast, market participants remain in the dark about the timing of unscheduled meetings. In line with Lucca and Moench (2015), we only consider scheduled meetings in this paper.

During the last 25 years, the Federal Reserve's communication strategy has gone through two major changes, and a number of other initiatives, all aimed at gradually increasing transparency. The first major change occurred in 1994, when the FOMC started to release a statement after any meeting that featured a policy rate change. Prior to 1994, FOMC monetary policy decisions were not announced, and investors had to infer policy actions through the size and type of open market operations in the days following each meeting. The second major change in FOMC communication strategy took place in May 1999, when the FOMC started to systematically release a post-meeting statement with the goal of signaling its future policy intentions. In sum, the timing of FOMC communication has become more consistent, and its content more transparent, since 1994. For these reasons, our baseline sample runs from 1994 until 2018.

2.2. Factor portfolios

In the empirical analysis we use factors that capture well know equity risk premiums such as size, value, momentum and low volatility. The factor returns are constructed from long-short portfolios. The equity returns data include all NYSE, AMEX, and NASDAQ stocks. We provide below a brief description of each factor:

- The market excess return (**Mkt-Rf**): the difference between Market return and risk-free rate is the daily excess return on the market. The risk-free rate corresponds to the one-month Treasury bill rate.
- The size factor (**SMB**; Small Minus Big): the return spread between low capitalization stocks and high capitalization stocks.
- The value factor (**HML**; High Minus Low): the return differential between value stocks and growth stocks.
- The profitability factor (**RMW**; Robust Minus Weak): the return differential between stocks with high operating profitability and stocks with low operating profitability.
- The investment factor (**CMA**; Conservative Minus Aggressive): the return differential between stocks with high asset growth and stocks with low asset growth.
- The momentum factor (**MOM**): the return differential of being long winners and short losers of the past 12 months and skipping the most recent month.
- The beta factor (**BETA**): the return differential of being long low market beta stocks and short high market beta stocks.
- The volatility factor (**VOL**): the return differential of being long low volatility stocks and short high volatility stocks.
- The idiosyncratic volatility (**IVOL**): the return differential of being long low idiosyncratic volatility stocks and short high idiosyncratic volatility stocks.[6]

The market, size and value factors have been staples of modern asset pricing models used in the literature at least since Fama and French (1993). The CMA and RMW factors proxy quality factors related to investment growth and profitability and have been introduced more recently (Fama and French, 2015). The BETA, VOL and IVOL factors capture a low volatility anomaly, and are related to the finding that stocks exhibiting lower volatility tend to achieve higher returns than

[5] In turn, the pre-FOMC announcement drift spurred a growing number of papers on FOMC-related anomalies (see, e.g., Bernile, Hu, & Tang, 2016; Cieslak, Morse, & Vissing-Jorgensen, 2018; Brusa, Savor, & Wilson, 2020). Hu, Pan, Wang, and Zhu (2022) propose a model that links the pre-announcement return directly to the accumulation of heightened uncertainty and its later resolution prior to the announcement to explain pre-FOMC returns. Liu, Tang, and Zhou (2022) develop a novel method to recover from options data the FOMC risk premium and drift sizes. In a recent contribution, Ben Dor and Rosa (2019) document that the pre-FOMC announcement drift is not statistically significant in the out-of-sample period of 2011–2017. In this study we argue that the FOMC anomaly should be analyzed conditional on Sentiment, rather than unconditionally.

[6] Following Ang, Hodrick, Xing, and Zhang (2006), idiosyncratic volatility is calculated relative to the Fama-French 3-factor model as the residual volatility from regressing a stock's excess returns on the Fama-French 3 factors.

those predicted by the Capital Asset Pricing Model.[7]

Table 1 reports the descriptive statistics of market and factor daily returns for the time period January 1994 to December 2018. The market and all the factors have positive average returns. The low volatility portfolios (BETA, VOL and IVOL) are the most volatile while CMA is the least volatile. RMW has the highest annualized Sharpe ratio (0.56), while the low volatility portfolios have some of the lowest annualized Sharpe ratios. Note that in the period under examination, the value, size and low volatility factors have significantly underperformed relative to the market on the basis of Sharpe ratios.

The low volatility factors display the largest maximum drawdowns (−91 % for BETA and −83 % and −76 % for VOL and IVOL, respectively). [8] While low volatility portfolios have performed well since inception in 1963, they underperformed during the last quarter of 2008 and they have not recovered yet, similar to what happened with momentum (Daniel and Moskowitz, 2016). In fact, low volatility strategies tend to lag in rising markets.

Table 2 reports two types of correlation measures among factor returns. The elements in the upper triangular matrix represent the Pearson product-moment correlation, which is designed to measure the strength of a linear relation between the two variables. The elements in the lower triangular matrix represent the rank (Spearman) correlation, which is designed to detect monotonicity in the relationship between the two variables. To enhance the clarity of the table, diagonal entries – which equal one – are left blank.

The US market return has a small positive correlation with the size factor and a negative correlation with all other factors, especially so with the low volatility portfolios. These correlation estimates suggest that factors can provide significant diversification benefits. Among the factors, BETA and VOL have the highest positive correlation. This is to be expected since both factors capture the low volatility anomaly. The size factor is negatively correlated with both RMW and low volatility portfolios. This result implies that the size factor is driven primarily by "weak" stocks that belong on the short leg of the quality factors, and low volatility portfolios tilt towards large capitalization stocks (Fama and French, 2016).

2.3. Investor sentiment

We measure investor sentiment using the monthly market-based sentiment series constructed by Baker and Wurgler, henceforth BW) (2006). The BW sentiment is calculated as the first principal component of five (standardized) sentiment proxies (e.g., closed-end fund discount, number of initial public offerings (IPOs), the average first day returns on IPOs, the dividend premium and equity share in new issues) where each of the proxies has first been orthogonalized with respect to a set of six macroeconomic indicators. The BW sentiment is a standardized index with mean zero and standard deviation one.

The time evolution of the sentiment index for the time period 1994–2018 is plotted in Fig. 1. The fluctuation of the sentiment index is consistent with a narrative approach of market booms and busts. It increased substantially prior to 2000, during the dot-com boom period, dropped after the Nasdaq crash, stabilized during the 2002–2007 period and decreased after the eruption of global financial crisis in 2008.

3. Results

3.1. Factor returns on FOMC announcement days

In this section we conduct an empirical analysis to examine the effect of the Federal Reserve monetary policy announcements on factor returns. To this end, we estimate the following baseline regression model for each factor portfolio:

$$R_t = \alpha + \beta \times \mathbf{1}(FOMC_t) + \varepsilon_t \tag{1}$$

where R_t is the daily factor portfolio return, and $\mathbf{1}(FOMC_t)$ is a dummy variable that takes the value 1 on scheduled FOMC meeting days, and 0 otherwise. The error term ε_t represents other factors that affect asset prices on event days and are assumed to be orthogonal to the explanatory variables of the regression. Eq. (1) posits that factor returns are time-varying. The coefficient α corresponds to the average return on non-event days, while $\alpha + \beta$ represents the average return on FOMC meeting days.

The coefficient estimates from the baseline regression are presented in Table 3. The regression for each factor return is estimated using ordinary least squares (OLS) with HAC standard errors (Newey and West, 1987) to account for autocorrelation and heteroskedasticity in the residuals. The dependent variable is measured in percent, so (for example) 0.1 means 10 basis points per day. CMA, RMW, BETA, VOL and IVOL have significantly negative returns on days of FOMC meetings. The average daily returns on FOMC announcement days range from − 5 basis points (CMA) to − 38 basis points (BETA).

To better gauge the empirical results we estimate regression (1) separately for the long and the short leg of each factor. Factor returns on FOMC announcement days tend to be negative because the short leg of factor portfolios tends to have higher returns compared to the long leg. For example, in the case of the IVOL factor the short leg has a positive return of 39 basis points and the long leg a positive return of 17 basis points on FOMC announcement days. Of note, the negative effect of FOMC announcements on factor returns is stronger for BETA, VOL and IVOL portfolios. This is because low volatility portfolios tend to hold high beta stocks on the short side.

3.2. Factor returns conditional on sentiment

Given the vast literature that examines the impact of behavioral biases on factor returns, we estimate a model of factor returns that also controls for sentiment:

$$R_t = \alpha_1 + \alpha_2 BWSent_{m-1} + (\gamma_1 + \gamma_2 BWSent_{m-1}) \times \mathbf{1}(FOMC_t) + \varepsilon_t \tag{2}$$

Where BW Sent_{m-1} stands for the previous month BW sentiment. We interact the FOMC dummy with the lagged BW investor sentiment variable to account for potential time-varying effects related to investor sentiment. Eq. (2) generalizes Eq. (1) when γ_2 is different from zero and indicates that the strength of the time variation is related to the sentiment variable. The results regarding factor returns are reported in Table 4. The coefficient estimates suggest that sentiment is significantly related to factor returns on FOMC announcement days. The γ_2 is positive for all factors and significant for RMW, MOM, BETA, VOL and IVOL. The point estimates indicate that a one standard deviation increase in the BW sentiment increases factor returns on FOMC announcement days between 16 basis points (RMW) and 63 basis points (VOL). Although factor returns are, on average, negative on FOMC announcement days, returns vary strongly with sentiment.[9] The effect of previous month BW sentiment on factor returns during non-FOMC days does not seem to be particularly significant. The coefficient α_2 is statistically significant for RMW and only marginally significant (at the 10 %level) for VOL and IVOL.

Table 4 reports also the coefficient estimates of regression (2) separately for the long and short leg of each factor portfolio. The results in Table 4 reaffirm that sentiment exerts a much higher influence on the short portfolio leg of factor portfolios. In the case of the long portfolio

[7] Ken French provides a rich data library containing the time-series data for various risk portfolios, including Mkt-Rf, SMB, HML, RMW and CMA. Lu Zhang data library provides the BETA, VOL and IVOL factors.

[8] Maximum drawdown is defined as the largest peak-to-trough decline during the sample period.

[9] As a robustness check, we also estimate Eq. (2) by controlling for sentiment as an additional regressor, and the results continue to hold.

Table 1
Summary statistics of daily factor returns.

	Mkt-Rf	SMB	HML	RMW	CMA	MOM	BETA	VOL	IVOL
Mean (%/d)	0.03	0.00	0.01	0.02	0.01	0.02	-0.01	0.01	0.02
Median (%/d)	0.06	0.02	0.00	0.01	0.00	0.06	-0.07	-0.04	-0.03
Maximum (%/d)	11.35	4.49	4.83	4.40	2.53	7.01	10.27	12.36	10.24
Minimum (%/d)	-8.95	-4.32	-4.22	-2.92	-5.93	-8.21	-21.88	-21.60	-19.69
Std. Dev. (%/d)	1.15	0.59	0.62	0.48	0.43	0.90	1.78	1.85	1.56
Skewness	-0.14	-0.14	0.43	0.29	-0.47	-0.85	-0.39	-0.22	-0.26
Kurtosis	10.85	6.40	11.25	9.78	14.02	13.24	11.13	11.64	13.70
Sharpe Ratio (ann.)	0.43	0.12	0.21	0.56	0.38	0.40	-0.12	0.09	0.18
Max Drawdown (%)	-59.28	-46.03	-41.36	-40.91	-21.27	-63.70	-90.90	-82.86	-75.74
1st-order Serial Correl.	-0.04	0.02	0.03	0.12	0.07	0.14	0.08	0.09	0.12
Observations	6294	6294	6294	6294	6294	6294	6294	6294	6294

Note: The sample is from January 1994 to December 2018. The Table reports the summary statistics for US daily portfolio returns. The daily returns are in percent, so (for example) 0.1 means 10 basis points per day. The Sharpe ratio is annualized using the square root of 252.

Table 2
Correlation matrix of portfolio returns.

	Mkt-Rf	SMB	HML	RMW	CMA	MOM	BETA	VOL	IVOL
Mkt-Rf		0.02	-0.05	-0.40	-0.34	-0.22	-0.70	-0.67	-0.55
SMB	0.08		0.05	-0.30	0.04	0.02	-0.23	-0.31	-0.37
HML	-0.15	0.03		0.08	0.50	-0.34	0.20	0.23	0.24
RMW	-0.34	-0.28	-0.00		0.26	0.15	0.60	0.65	0.67
CMA	-0.24	0.04	0.49	0.05		0.04	0.50	0.54	0.52
MOM	-0.00	0.01	-0.20	0.12	-0.06		0.27	0.27	0.25
BETA	-0.66	-0.29	0.23	0.50	0.32	0.06		0.88	0.81
VOL	-0.61	-0.40	0.25	0.54	0.36	0.07	0.83		0.94
IVOL	-0.50	-0.47	0.22	0.55	0.31	0.09	0.75	0.92	

Note: The sample is from January 1994 to December 2018. The level (Pearson) correlation between pairs of US daily portfolio returns is reported in the upper triangular matrix, the rank (Spearman) correlation is reported in the lower triangular matrix.

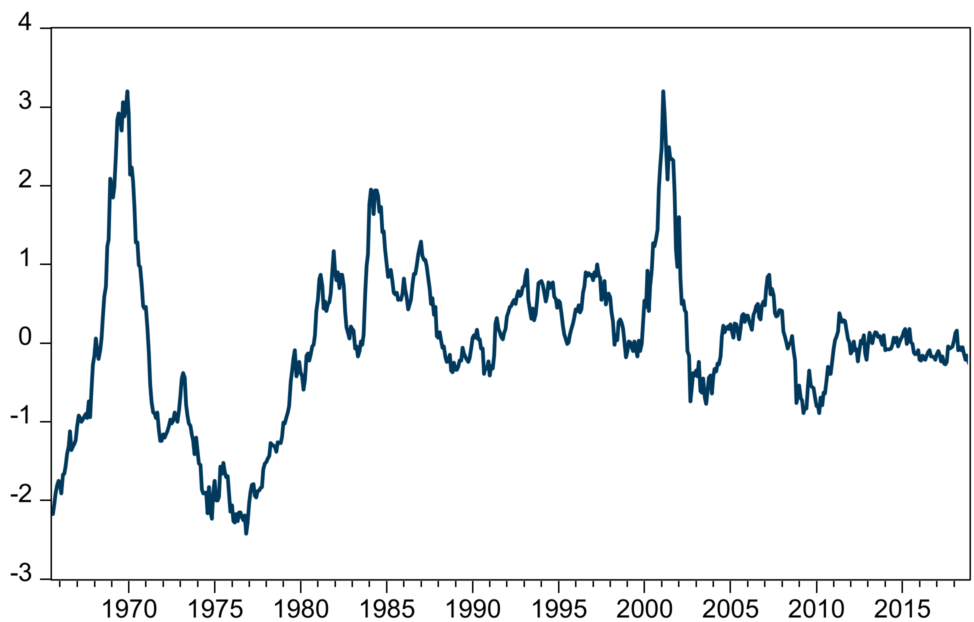

Fig. 1. Time series plot of Baker and Wurgler (2006) Investor Sentiment Index. Note: The sample is from July 1965 to December 2018.

leg the sentiment coefficient is insignificant in most cases, while the coefficients of the short leg are negative (especially in BETA, VOL, IVOL) and statistically significant in all factor portfolios.

The coefficient estimates from the long leg and the short leg portfolios suggest that factor returns on FOMC announcement days vary with sentiment mainly because of variation in the return of the short leg with respect to market sentiment, i.e., the return of the short leg tends to be higher than the return of the long leg following low sentiment levels while the return of the short leg tends to be lower than the return of the long leg following high sentiment levels.

As a robustness check, we examine the state dependence in factor returns to sentiment by conditioning on a high- and low-sentiment periods, rather than on a continuous variable. Specifically, a Low sentiment dummy takes value one when the previous month sentiment is in the bottom 50 % of the entire sentiment series during the period 1965–2018, and zero otherwise. Then, we re-estimate regression (2) using the sentiment state dummy (results available in a separate Appendix). The returns of RMW, MOM, BETA, VOL and IVOL are significantly negative on FOMC days only when the announcement occurs after low sentiment states and insignificant when the announcement occurs after high sentiment states (expect MOM). The point estimates range from − 17 basis points (for RMW) to − 55 basis points (for BETA). The decomposition of total factor returns into long portfolio returns and short portfolio returns provides some useful insights. The long leg portfolio return has insignificant returns

Table 3
Factor Returns on FOMC Announcement Days.

	Long-Short		Long leg		Short leg	
Factor	FOMC dummy	Constant	FOMC dummy	Constant	FOMC dummy	Constant
SMB	0.01	0.00	0.28***	0.04**	0.26***	0.03**
HML	0.04	0.01	0.30***	0.04**	0.26***	0.03**
RMW	-0.07**	0.02***	0.23***	0.04***	0.31***	0.02
CMA	-0.05*	0.01**	0.25***	0.04***	0.30***	0.03*
MOM	-0.02	0.02*	0.28***	0.05***	0.30***	0.02
BETA	-0.38***	-0.00	0.10	0.03***	0.48***	0.03
VOL	-0.37***	0.02	0.11*	0.04***	0.47***	0.01
IVOL	-0.21**	0.02	0.17***	0.04***	0.39***	0.01

Note: The sample is January 1994 to December 2018. The FOMC dummy takes value 1 on FOMC meeting days, and 0 otherwise. The econometric method is ordinary least squares with heteroskedasticity and autocorrelation-consistent standard errors. The superscripts ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 4
Factor Returns on FOMC Announcement Days Conditional on Investor Sentiment.

	Long-Short				Long				Short			
	FOMC	FOMC × BWSent	BWSent	Const	FOMC	FOMC × BWSent	BWSent	Const	FOMC	FOMC × BWSent	BWSent	Const
SMB	0.01	0.03	0.00	0.00	0.32***	-0.21	-0.01	0.04**	0.31***	-0.24*	-0.02	0.04***
HML	0.05	-0.03	0.04**	-0.00	0.35***	-0.27**	0.00	0.04**	0.31***	-0.24*	-0.03	0.04**
RMW	-0.11***	0.16***	0.04***	0.01	0.27***	-0.18	-0.00	0.04***	0.38***	-0.34**	-0.05	0.03*
CMA	-0.07**	0.06	0.02	0.01	0.29***	-0.20*	-0.02	0.04***	0.36***	-0.27*	-0.03	0.04**
MOM	-0.08	0.30**	0.03	0.02	0.31***	-0.16	-0.01	0.05***	0.39***	-0.46**	-0.04	0.03
BETA	-0.50***	0.57**	0.09	-0.02	0.12*	-0.09	0.01	0.03***	0.62***	-0.66***	-0.08	0.05*
VOL	-0.50***	0.63**	0.11*	0.00	0.12**	-0.04	-0.00	0.04***	0.61***	-0.68**	-0.11*	0.04
IVOL	-0.33***	0.57***	0.11*	0.00	0.19***	-0.06	-0.00	0.04***	0.52***	-0.63**	-0.11*	0.04

Note: The sample is January 1994 to December 2018. The FOMC dummy takes value 1 on FOMC meeting days, and 0 otherwise. The BW Sent variable stands for the one-month lagged orthogonalized sentiment index. Baker and Wurgler (2006) construct the orthogonalized sentiment index by regressing each of their six raw sentiment proxies on macroeconomic variables and then obtaining the first principal component of the regression residuals. The econometric method is ordinary least squares with heteroskedasticity and autocorrelation-consistent standard errors. The superscripts ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 5
Decomposition of the Sharpe ratio.

	Mkt-Rf	SMB	HML	RMW	CMA	MOM	BETA	VOL	IVOL
All days	0.43	0.12	0.21	0.56	0.38	0.40	-0.12	0.09	0.18
All days excluding FOMC days when BWSent < Median	0.36	0.12	0.19	0.65	0.41	0.45	-0.02	0.18	0.26

Note: The sample is from January 1994 to December 2018. The Table reports the annualized Sharpe ratio. The FOMC dummy takes value 1 on FOMC meeting days, and 0 otherwise. The BW Sent variable stands for the orthogonalized sentiment index. Baker and Wurgler (2006) construct the orthogonalized sentiment index by regressing each of their six raw sentiment proxies on macroeconomic variables and then obtaining the first principal component of the regression residuals. We compute the annualized Sharpe ratio as $\sqrt{252}$ times the daily Sharpe ratio (sample mean of portfolio return divided by its sample standard deviation) for the first row, and by multiplying the daily Sharpe ratio by $\sqrt{252-4}$ for the second row.

after low sentiment periods in all factors under consideration, while the short leg of the MOM, BETA, VOL and IVOL factors has positive returns, at the 5 % or 10 % significance level, after low sentiment periods.

Our findings indicate that factor returns on FOMC announcement days are time-varying and depend on sentiment. To assess the economic significance of the time-variation, we compute Sharpe ratios of factor portfolios in two samples: (i) all days and (ii) all days excluding those FOMC announcement days that occur in low sentiment periods. As before, we classify a period as a low sentiment period when the BW sentiment is below its median value. Table 5 indicates that for most factor returns the Sharpe ratios improve when we exclude FOMC announcement days following low sentiment periods. For instance, the Sharpe ratio of RMW increases from 0.56 to 0.65, for CMA increases from 0.38 to 0.41, for MOM increases from 0.40 to 0.45, and for IVOL increases from 0.18 to 0.26.

4. Robustness tests

We run several robustness checks. First, we repeat the exercise by controlling for systematic risk using Fama-French three-factor model as a benchmark. Second, we consider a large array of testing portfolios extending the number of factors to 185 different long-short factor portfolios. Finally, we look at different types of macro announcement news.

4.1. Factor returns conditional on fama-french three-factor model

We re-estimate the baseline regression (2) by also controlling for the Fama-French three-factor model. The results are reported in Table 6. The market betas of all factor returns are negative and statistically significant. The decomposition of factor returns into long and short portfolio returns sheds further light. Conditional on FOMC days, the long portfolio legs of factor return have a positive, but in most cases insignificant, coefficient with respect to sentiment, while short portfolio legs have negative and significant coefficients. The coefficient of factor returns with respect to lagged BW Sent on non-FOMC days is not statistically significant.

The long/short decomposition also shows that factor returns have negative market betas because the short leg of the portfolios has a higher positive market beta than the long leg of the portfolios. All long portfolio legs have market betas lower than 1 and all short portfolio legs have market betas higher than 1. The negative betas and the fact that market returns tend to be positive on FOMC announcement days (Lucca and

Table 6
Benchmark-Adjusted Factor Returns on FOMC Announcement Days.

	RMW	CMA	MOM	BETA	VOL	IVOL
Long-Short						
Constant	0.02***	0.01***	0.02*	0.01	0.04**	0.03**
BWSent	0.04***	0.00	0.04	0.04	0.05	0.07*
FOMC	-0.06**	-0.05*	-0.00	-0.20**	-0.20**	-0.13*
FOMC × BWSent	0.14***	0.05	0.24**	0.36**	0.43***	0.45***
Mkt-Rf	-0.16***	-0.12***	-0.19***	-1.05***	-1.04***	-0.72***
SMB	-0.24***	0.02	0.06	-0.67***	-0.97***	-1.00***
HML	0.06*	0.33***	-0.52***	0.50***	0.65***	0.59***
Adj. R^2	0.26	0.35	0.18	0.56	0.58	0.49
Long Leg						
	RMW	**CMA**	**MOM**	**BETA**	**VOL**	**IVOL**
Constant	0.01***	0.01***	0.02***	0.01*	0.02***	0.02***
BWSent	0.02***	0.01	0.02**	0.02	0.01	0.02
FOMC	-0.02*	-0.02	0.01	-0.05	-0.05*	-0.03
FOMC × BWSent	0.04**	0.02	0.06	0.04	0.09	0.12**
Mkt-Rf	0.95***	0.98***	0.99***	0.53***	0.54***	0.71***
SMB	0.33***	0.47***	0.50***	-0.11***	-0.16***	-0.22***
HML	0.07***	0.19***	-0.12***	0.17***	0.15***	0.10***
Adj. R^2	0.98	0.97	0.94	0.57	0.65	0.77
Short Leg						
	RMW	**CMA**	**MOM**	**BETA**	**VOL**	**IVOL**
Constant	-0.00	0.00	-0.01	-0.00	-0.02	-0.01
BWSent	-0.01*	0.00	-0.02	-0.02	-0.04	-0.05
FOMC	0.04*	0.03**	0.02	0.15***	0.15**	0.10*
FOMC × BWSent	-0.09***	-0.02	-0.17**	-0.32***	-0.34***	-0.33***
Mkt-Rf	1.11***	1.09***	1.18***	1.58***	1.58***	1.43***
SMB	0.57***	0.45***	0.44***	0.56***	0.81***	0.78***
HML	0.01	-0.14***	0.40***	-0.33***	-0.50***	-0.49***
Adj. R^2	0.96	0.98	0.86	0.83	0.81	0.81

Note: The sample is January 1994 to December 2018. The FOMC dummy takes value 1 on FOMC meeting days, and 0 otherwise. The econometric method is ordinary least squares with heteroskedasticity and autocorrelation-consistent standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Benchmark-adjusted factor returns (Double Clustering).

	All	Momentum	Value	Profitability	Frictions	Investment	Intangibles
Long-Short							
Constant	0.02***	0.02***	0.01	0.03***	0.01**	0.02***	0.02***
BWSent	0.02*	0.01	0.01	0.04***	0.02	0.00	0.02**
FOMC	-0.01	0.02	-0.05	0.00	-0.12***	-0.03	0.02
FOMC × BWSent	0.10**	0.24***	0.06	0.11	0.15*	0.05	-0.00
Mkt-Rf	-0.11***	-0.08***	-0.12***	-0.14***	-0.38***	-0.09***	-0.01
SMB	-0.08***	-0.12***	0.17***	-0.38***	-0.20	-0.03	0.14**
HML	0.06*	-0.27***	0.77***	-0.20***	0.32***	0.19***	-0.07
Adj. R^2	0.02	0.04	0.27	0.12	0.15	0.04	0.01
Number of Factors	185	40	32	44	10	29	30
Long Leg							
	All	**Momentum**	**Value**	**Profitability**	**Frictions**	**Investment**	**Intangibles**
Constant	0.02***	0.01***	0.01***	0.02***	0.01***	0.01***	0.02***
BWSent	0.01***	0.01	0.01	0.02***	0.01**	0.00	0.02***
FOMC	0.01	0.03	-0.01	0.01	-0.04***	-0.00	0.02
FOMC × BWSent	0.01	0.06*	0.02	0.01	0.01	-0.00	-0.02
Mkt-Rf	1.01***	1.04***	0.99***	1.00***	0.83***	1.02***	1.04***
SMB	0.15***	0.16***	0.26***	-0.02	0.17	0.18***	0.23***
HML	-0.12***	-0.24***	0.36***	-0.33***	0.01	-0.11***	-0.20***
Adj. R^2	0.78	0.80	0.76	0.86	0.69	0.83	0.76
Short Leg							
	All	**Momentum**	**Value**	**Profitability**	**Frictions**	**Investment**	**Intangibles**
Constant	-0.00	-0.00	0.01**	-0.01*	0.00	-0.00	-0.00
BWSent	-0.01	-0.00	0.00	-0.03**	-0.02	0.00	-0.00
FOMC	0.02	0.02	0.04**	0.01	0.08***	0.03	0.00
FOMC × BWSent	-0.09***	-0.18***	-0.04	-0.10*	-0.15**	-0.05*	-0.02
Mkt-Rf	1.11***	1.11***	1.11***	1.14***	1.21***	1.10***	1.05***
SMB	0.23***	0.28***	0.09***	0.35***	0.37***	0.21***	0.09***
HML	-0.18***	0.03	-0.41***	-0.13***	-0.30***	-0.30***	-0.14***
Adj. R^2	0.81	0.77	0.89	0.83	0.78	0.85	0.78

Note: The sample is January 1994 to December 2018. The FOMC dummy takes value 1 on FOMC meeting days, and 0 otherwise. The econometric method is ordinary least squares with double clustering standard errors. The superscripts ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 8
Benchmark-adjusted factor returns on macroeconomic announcement days.

	RMW	CMA	MOM	BETA	VOL	IVOL
Long-Short						
Constant	0.02***	0.01**	0.02*	0.01	0.03**	0.03**
BWSent	0.04***	-0.00	0.03	0.04	0.05	0.06
Ann. Days	-0.03*	0.01	0.00	-0.00	-0.04	-0.08*
Ann. Days × BWSent	0.01	0.05*	0.16**	0.11	0.19*	0.21**
Mkt-Rf	-0.16***	-0.12***	-0.19***	-1.05***	-1.04***	-0.72***
SMB	-0.24***	0.02	0.06	-0.67***	-0.97***	-1.00***
HML	0.06*	0.33***	-0.52***	0.50***	0.65***	0.59***
Adj. R^2	0.26	0.35	0.18	0.56	0.58	0.49
Long Leg						
Constant	0.01***	0.01***	0.02***	0.01	0.02***	0.02***
BWSent	0.02***	0.00	0.02*	0.02	0.01	0.01
Ann. Days	-0.01*	0.01	-0.00	0.00	-0.00	-0.04**
Ann. Days × BWSent	-0.00	0.02	0.06*	0.02	0.03	0.09*
Mkt-Rf	0.95***	0.98***	1.00***	0.53***	0.54***	0.71***
SMB	0.33***	0.47***	0.50***	-0.11***	-0.16***	-0.22***
HML	0.07***	0.19***	-0.12***	0.17***	0.15***	0.09***
Adj. R^2	0.98	0.97	0.94	0.57	0.65	0.77
Short Leg						
Constant	-0.00	0.00	-0.00	0.00	-0.01	-0.01
BWSent	-0.01*	0.01	-0.01	-0.02	-0.04	-0.05
Ann. Days	0.01	0.00	-0.00	0.01	0.03	0.04
Ann. Days × BWSent	-0.01	-0.03*	-0.10**	-0.09	-0.16**	-0.11*
Mkt-Rf	1.11***	1.09***	1.18***	1.58***	1.59***	1.43***
SMB	0.57***	0.45***	0.44***	0.56***	0.81***	0.78***
HML	0.01	-0.14***	0.40***	-0.33***	-0.50***	-0.49***
Adj. R^2	0.96	0.98	0.86	0.83	0.81	0.81

Note: The sample is January 1994 to December 2018. Ann. Day is a dummy variable taking value 1 if day t is an announcement day (nonfarm payroll or PPI), and 0 otherwise. The econometric method is ordinary least squares with heteroskedasticity and autocorrelation-consistent standard errors. The superscripts ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Moench, 2015) explain part of the negative factor returns.

The beta differential between long and short portfolio legs combined with the fact that the short leg generates sentiment-driven time variation of factor returns on FOMC announcements days is consistent with previous studies that examine the relationship between the security market line and sentiment. For instance, Antoniou, Doukas, and Subrahmanyam (2016) find that the security market line is positively sloped during pessimistic periods and downward sloped during optimistic periods. They argue that high beta stocks become overpriced during optimistic periods because these stocks attract less skilled and overconfident traders, while in pessimistic period noising trading is less prevalent and beta risk becomes more important as a determinant of equity returns.

4.2. Cross section of anomaly portfolios

To assess to what extent the results above hold across anomalies, we consider a large array of testing portfolios. Specifically, we build on the data library developed by Hou et al. (2020), who provide 185 factor returns, grouped into six themes: momentum (40), value (32), profitability (44), trading frictions (10), investment (29) and intangibles (30).[10] These anomalies encompass the bulk of the published anomalies literature in accounting and finance. We estimate the following panel regression:

$$R_{i,t} = \alpha_1 + \alpha_2 BWSent_{m-1} + (\gamma_1 + \gamma_2 BWSent_{m-1}) \times \mathbf{1}(FOMC_t) + \beta_1 Mkt\text{-}Rf_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t} \quad (3)$$

Where $R_{i,t}$ is the return on day t for anomaly i, the coefficients α, γs and βs are the same across equations, and the rest of the notation is the same as before. The standard errors of the coefficients are computed using double clustering, The cross-sectional cluster is formed by factor i.e., for each factor portfolio (185 portfolios) and by time. When errors are correlated, OLS remains consistent, but OLS standard errors tend to underestimate statistical uncertainty. Double clustering corrects the standard errors for correlation across factor returns and correlation of factor returns across time.

Table 7 reports the estimation results for all anomalies (first column, labelled "All") and by theme. Those anomalies display on average a positive and significant alpha of 0.02 % per day, resulting in an annualized return of about 5 %. The coefficient of sentiment is positive and significant when all factors are pooled together. The point estimate suggests that a decrease of one standard deviation in sentiment decreases the return of all portfolios by around 10 basis points on FOMC announcement days.

When the anomalies are grouped by theme, we find that the coefficient is significant for momentum and frictions. The bottom of Table 7 reports the results for the long and short leg separately. The long portfolio legs have insignificant coefficients with respect to sentiment (except momentum), while the short portfolio legs of momentum, frictions and profitability and investment portfolios have significant negative sentiment coefficients. We find that a decrease of one standard deviation in the BW

[10] The momentum anomalies capture the tendency for rising asset prices to rise further. Momentum anomalies use various formation periods for computing past returns, instead of an 11-month period ending one month prior to the rebalance date, as used in the MOM factor. Similarly, Value, Profitability and Investment anomalies are based on various valuation measures related to value-vs-growth, profitability and investment. Trading frictions capture the low volatility effect, while Intangibles capture prior investments in intangible assets (e.g., R&D capital-to-assets, R&D expense-to-sales or expense-to-market, operating leverage, asset liquidity, etc.).

sentiment increases the return of the short portfolio leg by 18 basis points (momentum), 10 basis points (profitability), 15 basis points (frictions) and 5 basis points (investment) on FOMC announcement days. One possible explanation as to why these four categories are related to sentiment on FOMC announcement days may be related to the fact that frictions, profitability and momentum have the highest market beta on their short portfolio leg. Previous studies have shown that high beta stocks are harder to value and more prone to sentiment. For example, Hong and Sraer (2016) show theoretically and confirm empirically, that high-beta stocks are more sensitive to investor disagreement about stock market earnings and are also more sensitive to speculative overpricing due to short-sale constraints compared to low beta stocks. Another possible explanation for the non-significance of value, investment and intangibles may be related to noise in factor constructions.

For some factors, Hou et al. (2020) consider three different holding periods of either 1-month, 6-month, or 12-month. They treat these as separate factors although they are based on the same sorting variable. To avoid double counting, we re-do the analysis by restricting the set of factors to those with 1-month holding period, as most of the original studies use. Moreover, the one-month holding period is intuitively appealing because it relies on the most current pricing data. By doing so, we reduce the set of anomalies from 185 to 117. Importantly, all the results (available in a separate Appendix) continue to hold even if we consider a subset of anomalies.

4.3. Factor returns on macroeconomic announcements days

Savor and Wilson (2013) show that stock market returns are significantly higher on days when important macroeconomic news about inflation, unemployment, or interest rates is scheduled for announcement. To test whether sentiment generates time variation in factor returns only on FOMC days or more broadly for other prescheduled monthly macroeconomic news announcements, we generate an announcement day dummy that takes value one on days when the producer price index (PPI) or employment figures are released. We use regression (3) and the results are reported in Table 8. The regression coefficients confirm that sentiment generates time variation in factor returns not only on FOMC announcement days but also on other macroeconomic announcement days. Like the previous results in the paper, the sentiment coefficients of the short portfolio leg are larger in magnitude (in absolute terms) compared to the coefficients of the long leg. The fact that sentiment is a significant driver of factor returns on three different macroeconomic news announcement days supports the view that the sentiment effect is a manifestation of an announcement effect and not an effect related to a pre-announcement drift.

5. Conclusion

Modern asset allocation strategies have embraced the idea of factor investing and tilt portfolios to harvest premiums related to size, value, momentum, low risk and quality. The popularization of factor investing has led to an enormous growth in “smart beta” strategies provided by a plethora of ETFs. The failure of traditional asset pricing models like the CAPM to explain the returns of factor portfolios poses a serious challenge from both an academic and a practitioner’s point of view.

To better understand the driving forces of factor premiums, we examine the return response of factors during FOMC announcement days. On FOMC announcement days market participants need to process new important information and price stocks accordingly. The empirical results show that the return response of factors depends on the prevailing market sentiment. For most factors employed in the empirical analysis, the short leg is more sensitive to market sentiment on FOMC announcement days compared to the long portfolio. When market sentiment is low, factor returns tend to be lower because the short portfolio tends to outperform the long portfolio leg. In all factors considered in the empirical analysis, the short portfolio leg that invests in relative “overpriced” stocks has higher market beta risk compared to the long leg that invests in relative “underpriced securities”.

The pattern in betas combined with the sentiment-driven time variation of factors returns, suggests that stock returns on FOMC announcement days are positively related to beta risk after low sentiment periods. The pattern in market betas of the long and short portfolio legs is an interesting phenomenon that has not received much attention in the literature and deserves further investigation. This pattern suggests that a common mispricing factor positively related to beta may underlie all factor returns.

Declaration of Competing Interest

No potential conflict of interest is reported by the authors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.qref.2024.03.014.

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