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Central Bank Information Shocks, Value Gains, and Value Crashes

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Abstract

Monetary policy shocks that convey new macroeconomic information are significant predictors of both the absolute and risk-adjusted returns from value investing. Positive Fed information shocks lead to higher subsequent value returns. Crashes in the returns of value investing are most likely to occur in the aftermath of negative Fed information shocks. The effect of Fed information shocks on value returns and crashes is to a large extent driven by these shocks' impact on informed trading. In practical terms, information shocks by the Fed are more impactful than conventional monetary shocks, and should hence be more prioritized by value investors.

Keywords: Value Premium; Federal Reserve; Information Shocks; Stock Crashes.
JEL classification: G11; G12; G14; E52; E58.

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1. Introduction

Value investing remains a prominent investment style, with adherents in both academia and the financial sector (Lakonishok, Shleifer, and Vishny 1994; Golubov and Konstantinidi 2019; Kok, Ribando, and Sloan 2016; Asness, Moskowitz, and Pedersen 2013). The high wealth gains from value stocks are widely documented in previous scholarly work which shows that this performance is not fully explained by risk factors (La Porta et al. 1997; Petkova and Zhang 2005; Piotroski and So 2012). The mispricing-based explanations of this phenomenon attribute these gains to the correction of underpricing that is primarily driven by investor underreaction, extrapolation of past returns, and expectation errors (Piotroski and So 2012; Lakonishok, Shleifer, and Vishny 1994). Recent evidence by Golubov and Konstantinidi (2019) reinforces the notion that underpricing is an integral contributor to the gains from value investing.

The literature recognizes that the mispricing of value stocks persists for a considerable period before being eventually adjusted by corrective market forces (DeLong et al. 1990; Shleifer and Vishny 1997; Barberis and Thaler 2003). However, the particular conditions that lead information-driven investors to alleviate this mispricing remain to be examined. This examination is particularly relevant because, despite their presumed underpricing, value portfolios can still experience periods of considerable underperformance, large losses, and poor risk-adjusted returns (Kok, Ribando, and Sloan 2016). Our main contribution in this paper is to specify predetermined, conditional, and publicly available informational factors that increase the likelihood of the value portfolios displaying significant gains (losses).

To address this issue, we appeal to the influence of a highly consequential informational player: the Federal Reserve (hereafter "the Fed"). While the Fed is known as the executor of monetary policy in the traditional sense, it has also managed to establish itself as a credible source of new macroeconomic market-moving information (Adra 2021; Jarociński and Karadi 2020; Nakamura and Steinsson 2018). For example, the dedication of considerable resources to economic forecasting allows the Fed to produce more reliable inflation forecasts than those provided by private forecasters (Romer and Romer 2000). Likewise, Nakamura and Steinsson (2018) show that the information conveyed by the Fed's announcement leads private investors to update their belief about the entire macroeconomic outlook.

Our main prediction builds on the theoretical model of Dow, Goldstein, and Guembel (2017) suggesting that positive fundamentals reduce the concerns of equity investors and incentivize them to increase informed trading, which is a necessary condition for alleviating mispricing (Kumar 2009). In the context of our analysis, by conveying positive news about the economic outlook, the Fed contributes to the rise in the informed trading needed to realize the gains from the value portfolio. In particular, by providing a reassuring view about the macroeconomic environment, the Fed reduces the concerns of equity investors about the economic outlook. Such assurance allows investors to expend more resources in adjusting the mispricing of hard-to-value firms like value companies. In contrast, a negative assessment of the economic outlook by the Fed deters equity investors from informed trading, hence reducing both the absolute and risk-adjusted gains from value investing.

Our analysis of the Fed information shocks' effects on absolute returns, crashes, and risk-adjusted performance of value portfolios supports our empirical prediction. To identify Fed information shocks, we follow recent studies (Jarociński and Karadi 2020; Breitenlechner, Gründler, and Scharler 2021) that exploit the correlation between the S&P 500 and Fed funds futures at the times of announcements made by the Federal Open Market Committee (hereafter "FOMC"). In this context, rises in interest rates that are associated with an increase in stock market returns, contrary to the scenario predicted by macroeconomic theory (Gertler and Karadi 2015; Bernanke and Kuttner 2005), are considered as positive information shocks. This is because such monetary tightening is treated by equity investors as a reassuring signal of the Fed's confidence in the macroeconomic outlook. Likewise, decreases in interest rates that are not associated with a positive stock market reaction are treated as negative Fed information shocks, as they reflect the Fed's concern about the economy.

We show that a standard deviation information shock conveying a positive (negative) assessment of the macroeconomic outlook predicts up to a 0.5% rise (decline) in the value portfolio's returns during the subsequent month. This effect holds after controlling for the effects of lagged portfolio returns and Fama and French (2015) risk factors. Further emphasizing the role of Fed information shocks in driving the gains (losses) from value investing, we show that the largest crashes in the returns of value portfolios are most likely to occur in the aftermath of negative Fed information shocks. Specifically, a standard deviation information shock conveying negative economic news increases (decreases) the chances of large crashes in value portfolio returns by more than 5%.

We also present robust evidence emphasizing the role of changes in informed trading as the key channel via which Fed information shocks influence the returns of value investing.

Using the time-varying changes in the non-synchronized trading proxy developed by Roll (1988), we show that (a) positive Fed information shocks contribute to a rise in the price non-synchronicity of value companies, (b) the positive lagged effect of these shocks on the value portfolio's returns is considerably weakened after controlling for the effect of the changes in price non-synchronicity, and (c) the reduction in the likelihood of crashes in the value portfolio in the aftermath of positive information shocks is to a large extent driven by the rise in this portfolio's price non-synchronicity. Put together, these results are aligned with our empirical prediction that the Fed's information shocks shape the value portfolio's performance through their impact on price informativeness.

In assessing the contribution of Fed information shocks to the risk-adjusted performance of value investing, we follow the approach used in Christopherson et al. (1998) by estimating conditional alphas while controlling for the effect of asset pricing factors. Evidence from our estimations suggests that the alphas of the value portfolio, based on the asset pricing models of Fama and French (1993, 2015), are driven by the lagged levels of Fed information shocks.

Our findings contribute to various strands of literature. Our most direct contribution is to enhance the understanding of determinants of value investing's performance from the perspective of both the equity premium prediction (Welch and Goyal 2007), conditional alphas (Christopherson, Ferson, and Glassman 1998), and stock price crash risk (Hutton, Marcus, and Tehranian 2009; Habib, Hasan, and Jiang 2018) literature. Our paper provides the first contribution that emphasizes the role of a pre-determined variable representing the Fed's information shocks in predicting both the absolute and risk-adjusted performance of value investing in addition to the likelihood of crashes in value portfolios.

Still, our findings should be treated with caution as they do not necessarily offer an edge for investors looking for market timing opportunities based on book-to-market sorts. Kok et al. (2016) criticize the exercise of mechanically selecting groups of high book-to-market companies. They argue that such a passive screening practice – while commonly promoted as part of value investing – is not necessarily compatible with the value investing philosophy developed in the classic work of Graham and Dodd (1934). For instance, investors might classify companies with inflated book values in the high book-to-market portfolio, and hence mistakenly treat them as value companies. Such classification leads investors to fall into "value traps", which consist of mistaking many high book-to-market companies for value investments.

As a result, Kok et al. (2016) argue that quantitative classification criteria are not substitutes for fundamentals-based analysis in the Graham and Dodd (1934) tradition.

Our findings do not refute, but rather stress, the necessity of conducting firm-specific security analysis to enhance the performance of passive value screening strategies to avoid value traps. Our main inference is that positive macroeconomic news increases the probability that the universe of high book-to-market companies contains sources of significant value creation, which moves the passive screener one step away from "value traps" without necessarily reaping gains after controlling for trading costs. But more importantly, a key implication of our findings is that such positive news facilitates the tedious task of fundamental analysts aiming to capture gains from undervalued firms. This is particularly relevant as information-driven investors, in the context of the Kyle (1985) model, can gain an advantage by taking positions in value stocks before their price impact causes value returns to move in their favor.

Our findings also provide novel evidence for the analysis of asset returns on the relevance of the Fed as a pertinent information producer. This consequential role has been recently highlighted in various scholarly areas. In the field of macroeconomics, contributions such as Nakamura and Steinsson (2018), Jarociński and Karadi (2020), and Breitenlechner et al. (2021) show that the Fed's information shocks have economic consequences that are qualitatively and quantitatively different than the effects of conventional ones. Breitenlechner et al. (2021), for instance, show that the expansionary effects of unconventional expansion are counteracted when expansionary policy conveys negative economic news. Nakamura and Steinsson (2018), in turn, show that economic growth forecasts increase in the aftermath of positive Fed information shocks. In the field of corporate finance, Adra (2021) shows that interest rate rises that covey positive economic information increase, rather than decrease, the Initial Public Offerings (IPO) activity.

Our value-based results expand this literature by adding a new area in which Fed information shocks are proven to be highly consequential in influencing financial outcomes. Interestingly, our findings suggest that the effects of Fed information shocks are larger and more statistically significant than the effects of conventional monetary policy shocks. These inferences testify to the importance of the Fed as an information producer, beyond its conventional function as executor of monetary policy, in influencing asset returns.

This paper proceeds as follows: Section 2 presents our main empirical predictions; Section 3 discusses our dataset which covers the returns of value portfolios and the commonly used asset pricing factors; Section 4 discusses the identification of information shocks by the Fed in addition to conventional monetary surprises; Section 5 presents our main results in addition to their related discussion and robustness checks, Section 6 emphasizes the extent to which these results are influenced by changes in informed trading, and Section 7 concludes.

2. Empirical Predictions

Classical models in information economics, such as Grossman and Stiglitz (1980) and Kyle (1985), depict active traders who invest resources in the acquisition of valuable information about the prospects of informationally demanding firms. These models predict that these traders are rewarded by significant returns in exchange for information-gathering efforts. Along similar lines, Kumar (2009) empirically shows that the presence of valuation difficulties leads information-driven investors to intensify their trading activity in an attempt to exploit the temporal bias-driven mispricing.

Value companies present an exemplary case of firms whose valuation is highly informationally challenging. These companies are perceived to be under high financial distress due to their either high financial leverage or uncertainty about future earnings (Chen and Zhang 1998; Avramov et al. 2013). Indeed, Avramov et al. (2013) present robust findings suggesting that the gains from value investing are largely driven by firms exposed to high financial distress risk. Nevertheless, the informational challenges arising from high financial distress risk make value firms subject to limited attention by investment analysts and make them less likely to occupy significant fractions of institutional investors' portfolios (Damodaran 2012). Moreover, the weak informational environment characterizing value companies makes their valuation more vulnerable to behavioral biases (Daniel, Hirshleifer, and Teoh 2001; Hirshleifer 2001). Nevertheless, the ambiguity surrounding the fate of value companies and their bias-driven mispricing provide a fertile ground for traders who are willing to invest substantial resources in assessing these companies' fundamentals (Leibowitz 2005; Frazzini, Kabiller, and Pedersen 2013).

Such tasks are highly demanding and by no means straightforward in the presence of an uncertain economic outlook, especially because assessing the growth prospects of difficult-to-value companies requires a clear understanding of the economic environment in which they operate. In its capacity as a larger producer and conveyer of macroeconomic information and forecasts, the Fed can alleviate part of these challenges. After all, macroeconomic information occupies half of the Fed's announcements (Cieslak and Schrimpf 2019). Moreover, the Fed is known to commit considerable resources to forecasting compared to commercial firms (Romer and Romer 2000). By conveying credible assessments of the economic outlook via FOMC announcements, the Fed can create a public good that reduces the investors' burden of expending significant resources on economic forecasts and facilitates their task in correcting the mispricing of firms with low market valuation.[1]

In assessing the impact of the information released by the Fed on the correction of prevailing mispricing, it is important to distinguish positive information shocks from negative ones. Most notably, the Dow, Goldstein, and Guembel (2017) model suggests that the value of speculative information increases substantially after positive information shocks and decreases after negative ones. This is because positive news about fundamentals reduces the likelihood of firms cancelling their projects, which incentives equity traders to expend more efforts in collecting more substantial information about the firm's growth prospects.

In the realm of value investing, this reasoning leads to a clear mechanism via which information shocks by the Fed end up influencing the returns of value portfolios. In particular, positive Fed information shocks are expected to increase the returns of value portfolios and reduce their likelihood of experiencing significant crashes. This effect is expected to be primarily driven by the positive influence of Fed information shocks on informed trading in value companies. Empirically, we test the following predictions:

Prediction 1: Fed information shocks conveying positive news increase the returns of value portfolios

Prediction 2: The effect of Fed information shocks on the performance of value portfolios is explained by the change in informed trading

[1] Recent evidence suggests that the positive Fed news shocks are followed by higher stocks returns, growing output, (Jarociński and Karadi 2020; Breitenlechner, Gründler, and Scharler 2021) and decreasing risk perceptions (Hattori, Schrimpf, and Sushko 2016).

3. Portfolio Data

The dataset covering the monthly returns of value/growth strategies and the risk factors is retrieved from Professor Kenneth French's website between February 1990 and December 2016, covering 323 monthly observations. This time window is chosen to ensure that the returns data overlaps with the Jarociński and Karadi (2020) dataset representing Fed information and regular shocks. Hi_10 is the return on the portfolio in the lowest book-to-market decile based on sorts conducted on all NYSE, AMEX, and NASDAQ stocks. A similar approach is used to construct Hi_20 and Hi_30 which refer to portfolios in the top 20% and 30% in terms of book-to-market valuation, respectively. Lo_10, Lo_20, and Lo_30 refer to the returns of portfolios in the bottom 10%, 20%, and 30% in terms of book-to-market valuation, respectively.

R_M is the monthly return of a value-weighted portfolio of all CRSP US incorporated companies listed in the NYSE, AMEX, or NASDAQ. SMB is the difference between the returns of a portfolio of small companies and a portfolio of large ones. In recent work, Fama and French (2015) propose the addition of profitability and investment to asset pricing models. RMW is the difference between a portfolio of high-profit companies and a portfolio of low-profit companies. CMA, in turn, is the difference between a diversified portfolio of low-investment firms and an alternative portfolio of high-investment ones. The detailed construction of these factors, as described on Kenneth French's website, is presented in Table 1.

(Insert Table 1 about here)

Table 2 reports the descriptive statistics of the variables used in our analysis. The overall patterns presented in this table suggest that, on average, value portfolios display higher average performance than both growth and market portfolios. For example, firms in the highest value decile experience average monthly returns of 1.15% relative to 0.86% for firms in the lowest decile and 0.88% for the overall market index. However, value portfolios also display higher average riskiness (6.26%) than the growth (4.71%) and market portfolios (4.28%).

(Insert Table 2 about here)

To further compare the gains from value investing relative to alternative strategies, we present in Figure 1 the cumulative dollar gains from $1 invested in the top value portfolio (Hi_10), growth portfolio (Lo_10), and the overall stock market. The first interesting observation from Figure 1 is that value investors realize substantial accumulated returns relative to growth and market investors and investors in risk-free US securities. Nevertheless, value investment experienced periods of large declines in returns in the early 2000s and the aftermath of the recent financial crisis. The main takeaway from these patterns is that the realization of gains from value portfolio is time-varying and by no means consistent, which raises the need for examining the specific conditions that influence the likelihood of gains realization, or for that matter extreme losses, from value portfolios.

(Insert Figure 1 about here)

4.Methods

4.1. Shock identification

For our identification of Fed information shocks and their separation from conventional ones, we follow the approach developed by Jarociński and Karadi (2020) and recently applied in Breitenlechner et al. (2021) and Adra (2021).

In the 30 minutes around each FOMC announcement (10 minutes before, 20 minutes after), interest rate changes that are negatively correlated with changes in the stock market (S&P 500) are considered as proxies for monetary shocks in the conventional sense. This is because unanticipated interest rate rises, as suggested in the monetary literature, reduce future lending and growth prospects, which consequently reduce stock returns (Thorbecke 1997; Bernanke and Kuttner 2005). We label these shocks as *Fed Conventional Shocks*. In turn, the interest rate changes that are positively correlated with the S&P 500 are classified as *Fed Information Shocks*. This is because an unanticipated interest rate increase can signal to equity investors that the Fed has a positive assessment of the economic outlook, which leads to higher stock returns (Jarociński and Karadi 2020; Breitenlechner, Gründler, and Scharler 2021). The separation of conventional and informational shocks is shown to assist the empiricist in resolving various empirical puzzles in the monetary literature (Miranda-Agrippino and Ricco 2021). We rely on the expansive Jarociński and Karadi (2020) dataset that covers 240 FOMC announcements between February 1990 and December 2016. Before 1994, the high-frequency movements in asset returns are measured when open-market operations take place on the following days as FOMC did not officially announce its decisions.

Figure 2 presents the scatterplot of Jarociński and Karadi (2020) where the interest rate and stock return surprises for each FOMC meeting are presented by a dot. The dots in the top-left and bottom-right quadrants, which cover 75% of the meetings, cover conventional monetary shocks as the rise (decline) in interest rates is associated with a decline (rise) in S&P 500 returns. In turn, dots in the top-right and bottom-left quadrants are aligned with the informational interpretation of Fed announcements whereby unanticipated increases (decreases) in interest rates convey a positive (negative) assessment of the economic outlook, which is reflected by a rise (decline) in S&P 500 returns. As our analysis covers monthly data, following Gertler and Karadi (2015) and Jarociński and Karadi (2020), the value of interest rate changes around the FOMC announcement is assigned for the calendar month in which the FOMC meeting took place. In the minority of cases where more than one FOMC meeting take place within one calendar month, the average value of the interest rate surprise is assigned to the month.

In introducing information and regular shocks to our empirical analysis, we build on Miranda-Agrippino and Ricco (2020) by recognizing the possibility of the slow processing of information by market investors (Coibion and Gorodnichenko 2015). Accordingly, we remove the potential autoregressive components in these shocks by using the first difference. Hence, Δ*Info* and Δ*Regular*, which refer to the monthly difference in information and regular shocks, are used as our main explanatory variables. The descriptive statistics of these variables are reported in Table 2.

4.2. Excess return and stock crash prediction

The first part of our empirical analysis assesses the ability of Fed information and regular shocks to predict the excess returns of value and growth portfolios. Specifically, we estimate the following specification:

$$\begin{aligned} r_{Portfolio} - r_f = \bar{\alpha} + \alpha_{Info}\Delta Info_{t-1} + \alpha_{Regular}\Delta Regular_{t-1} \\ + f(Lagged\ Factors_{t-1}) + \varepsilon_t \end{aligned} \tag{A.1}$$

where $r_{Portfolio}$ is the return of the corresponding portfolio (value or growth), and r_f is the one-month U.S. Treasury yield. $\bar{\alpha}$ is an intercept while $\Delta Info_{t-1}$ and $\Delta Regular_{t-1}$ represent the Fed information and regular shocks, respectively, as defined in the previous subsection. $f(Lagged\ Factors_{t-1})$ present the lagged effects which include the excess returns on the portfolio and Fama French (2015) risk factors, excluding the value factors to avoid spurious effects. ε_t is a white noise error term.

To further emphasize the Fed's impact on the performance of the portfolios that we examine, we modify Equation (A.2) to estimate the following Logit specification:

$$ln\left(\frac{Pcrash_t}{1-Pcrash_t}\right) = \bar{\alpha} + \alpha_{Info}\Delta Info_{t-1} + \alpha_{Regular}\Delta Regular_{t-1} + f(Lagged\ Factors_{t-1}) + \varepsilon_t \tag{A.2}$$

where $Pcrash_t$ is the probability of the portfolio experiencing returns below the 10th percentile in month t. The corresponding 10th percentile levels for the portfolios examined in this paper are as follows: -6.3% for Hi_10, -5.5% for Hi_20, -4.43% for Hi_30, -5.2% for Lo_10, -3.6% for Lo_20, and -4.66% for Lo_30. It is also worth noting that the results reported in this paper hold when the probability of declines below the 5th percentile are used as the dependent variable.

4.3. Conditional Alphas

To assess the impact of the Fed's informational and regular shocks on risk-adjusted performance, we estimate conditional alphas, as in Christopherson et al. (1998). This approach consists of examining how the alpha of a particular investment strategy varies with predetermined, conditional, and publicly available information. In the context of our analysis, this approach consists of introducing $\Delta Info_{t-1}$ and $\Delta Regular_{t-1}$ as additional regressors in models controlling for the Fama French factors. For instance, in Fama French specifications controlling for the size effect (HML is excluded to avoid spurious relations), the model is estimated as follows:

$$r_{Portfolio} - r_f = \bar{\alpha} + \alpha_{Info}\Delta Info_{t-1} + \alpha_{Regular}\Delta Regular_{t-1} + a_M(r_M - r_f)_t + a_{SMB}SMB_t + \varepsilon_t \tag{B.1}$$

whereby the Fama French alpha is:

$$\alpha = \bar{\alpha} + \alpha_{Info}\Delta Info_{t-1} + \alpha_{Regular}\Delta Regular_{t-1} \tag{B.2}$$

which includes a time-invariant component $\bar{\alpha}$ in addition to time-varying effects predicted by the lagged information and regular shocks. Our analysis is also expanded to include the richer specification from Fama and French (2015), which controls for the additional impacts of the investment (CMA) and profitability (RMW) factors as follows:

$$r_{Portfolio} - r_f = \bar{\alpha} + \alpha_{Info}\Delta Info_{t-1} + \alpha_{Regular}\Delta Regular_{t-1} + a_M(r_M - r_f)_t + a_{SMB}SMB_t + a_{CMA}CMA_t + a_{RMW}RMW_t + \varepsilon_t \tag{B.3}$$

5. Results and Discussion

5.1. Fed information shocks and the returns of value investing

The effects of regular and information shocks on the returns of value and growth portfolios are presented in Table 3. The evidence presented in this table offers various interesting results aligned with our first prediction. First, we find that Fed information shocks are significant predictors of the performance of value, rather than growth, portfolio. Second, the effects of Fed information shocks on excess returns increase with the stricter definitions of the value portfolio. When the value portfolio is defined based on companies in the top 30% of book-to-market valuations (Hi_30) the effect of Fed information shocks is positive but statistically insignificant. With stricter definitions of the value portfolio (i.e., firms in the top 20% and 10% of book-to-market valuations), these effects become stronger, statistically and economically. In particular, a standard deviation Fed information shock predicts a rise in the returns in the subsequent month by 0.42% and 0.53% for Hi_20 and Hi_10, respectively.

A third important observation from our results is that, in terms of the Fed's influence on the value portfolio returns, the information shocks are more impactful than the regular monetary shocks. Specifically, the effect of regular monetary shocks is statistically and economically insignificant in all the specifications that are reported. This result can be attributed to the widely documented time variation in the effects of conventional monetary policy on economic performance (Jansen and Zervou 2017; Pascal 2019). While the general direction of conventional shocks' economic impacts is quite predictable, the particular transmission of these effects remains highly uncertain. Accordingly, while Fed information shocks reduce the uncertainty about the economic outlook, such an effect is not necessarily associated with conventional monetary shocks. In Appendix 1, we track the effects of conventional and Fed information shocks for up to 12 months. We show that the effect of the information shocks on value returns is mainly captured within the first month that follows the shock.

(Insert Table 3 about here)

5.2. Fed information shocks and the crashes in value portfolios

Table 4 presents a set of Logit models based on the specification presented in Equation (A.2). The evidence presented in these models is aligned with the effects on excess returns documented above. That is, large Fed information shocks conveying positive (negative) macroeconomic news predict a significant decline (rise) in the likelihood of value stock returns falling below the 10th percentile in the subsequent month. In Model (6), a standard deviation increase in $\Delta Info_{t-1}$ (i.e., positive Fed information shock) reduces the likelihood of a crash in Hi_10 by 5%. The equivalent effects are 3% (insignificant) and 4% (significant at 10%) in Models (5) and (6) for Hi_30 and Hi_20, respectively. Despite the consistent negative effect on the performance of the growth portfolio, none of the effects of Fed information shocks is significant in Models (1), (2), and (3). The effects of regular Fed shocks, in turn, are insignificant in all the reported models.

These results suggest that, despite their presumed underpricing, value portfolios can still experience noticeable losses in the aftermath of negative Fed information shocks. As predicted by Dow et al. (2017), negative news about fundamentals can dissuade information-driven investors from the attempt to correct the prevailing mispricing. To the best of our knowledge, the specifications presented in Table 4 are the first in the literature that control for the effect of Fed information shocks on portfolio crash risk. Interestingly, as shown in the baseline specifications in Panel A and the extended ones in Panel B, these shocks are the only statistically significant predictors of the odds of value portfolio crashes. In the following subsection, we expand this analysis by assessing these shocks' predictive powers in evaluating the risk-adjusted performance of value investing.

(Insert Table 4 about here)

5.3. The conditional alphas of value investing

The role of informational and conventional central bank shocks in influencing the value alphas are reported in Tables 5 and 6. Table 5 controls for the market and size factors, as in Fama and French (1993), as depicted in Equation (B.1). Table 6 controls for the effects of the market, size, investment, and profitability factors as in Fama and French (2015), as depicted in Equation (B.3).

The evidence from both tables suggests that the conditional alphas of value portfolios are, to a large extent, shaped by the lagged effects of Fed information shocks. As in the case of absolute returns and the likelihood of crashes, the effects of information shocks on alphas are more pronounced in the case of portfolios in the top book-to-market decile. The evidence from Table 5 (Model (6)) shows that a standard deviation Fed information shocks increases the monthly value alpha by 0.36% from Hi_10. The equivalent effect is smaller for Hi_20 and Hi_30, where the rises in alpha are 0.27% and 0.17%, respectively. Moreover, the effect of Fed information shocks on conditional alphas in Model (4) is statistically weaker than these effects in Models (5) and (6).

(Insert Table 5 about here)

The evidence reported in Table 6 yields the same qualitative conclusions as those reported in Table 5 with the effect of Fed information shocks on value alphas being somewhat weaker in the presence of additional risk factors. A standard deviation Fed information shocks increases the monthly value alpha by 0.27% from Hi_10 in Model (6). The equivalent effect is smaller 0.20% in Model (5) for Hi_20. A smaller and statistically insignificant effect of 0.1% holds in Model (4) for Hi_30. Interestingly, the Fed information shocks do not substantially influence the conditional performance of the growth portfolios.

(Insert Table 6 about here)

The overall conclusion from our empirical results suggests that the Fed's information shocks considerably more influential on the value portfolio's performance, both statistically and economically, than monetary shocks in the conventional sense. The exclusive impact of Fed information shocks on value stocks, whose valuations are known for being informationally demanding, further testifies to the Fed's relevance as a producer of highly consequential information.

6. The Informed Trading Channel

Our second prediction emphasizes the change in informed trading as the primary channel via which the Fed's information shocks influence the performance of the value portfolio. In this section, we empirically highlight this channel by examining the extent to which Fed information shocks influence informed trading. We also examine whether the predictive impact of Fed information shocks on the performance of value portfolios continues to hold after controlling the effect of changes in informed trading. The presence of an informed trading channel, as discussed in our prediction, implies that (a) positive Fed information shocks should increase informed trading in value stocks, and (b) these shocks' impact on the returns of the value portfolio becomes insignificant after controlling the effects of changes in informed trading.

Our estimate of the degree of informed trading follows from the seminal contribution of Roll (1988). Roll's (1988) approach is derived from the observation that variations in stock returns are only modestly explained by the market index, industry factors, company size, and public announcements. Accordingly, Roll (1988) attributes non-synchronized trading in stocks, which is reflected in the variation in returns not explained by market factors, to informed trading activity by private investors. Such an approach has been vindicated in empirical research that attributes the synchronized variations in stock returns to factors such as sentiment (Baker and Wurgler 2006), style investing (Barberis and Shleifer 2003), and contagion (Kodres and Pritsker 2002), while attributing the non-synchronized variations to trading based on (mostly) privately collected information.

As our analysis is focused on the returns of aggregate portfolios, our application of the Roll (1988) approach for analyzing the returns of the value portfolio consists of first estimating the CAPM model:

$$(r_{Portfolio} - r_f)_t = a_1 + a_2(R_M - R_f)_t + \varepsilon_t \tag{C.1}$$

by using the daily observations in each calendar month for the growth portfolio (Lo_10) and the value portfolio (Hi_10), with ε_t representing a white noise error term. We consider the part of the variation in excess returns that is not explained by this model (i.e., $1 - R^2$) as a proxy for the level of price informativeness in each month. To avoid the potential impact of noisiness on our estimates, we adopt the following dummy variable approach: for the growth portfolio, we construct the variable $GrowthInfoRise$ which is assigned the value of 1 if the level of non-synchronized trading in the growth portfolio increases by more than 1% relative to the prior month, and 0 otherwise. Equivalently, $ValueInfoRise$ is assigned the value of 1 if the level of non-synchronized trading in the value portfolio increases by more than 1% relative to the prior month, and 0 otherwise. In the case of $GrowthInfoRise$, the value of 1 is assigned to 42% of the observations, while in the case of $ValueInfoRise$ this value is assigned to 48% of the observations.

Table 7 presents two logit models examining how Fed shocks, both conventional and informational, influence the odds of a rise in informed trading in the growth and value portfolios, respectively. As predicted, positive Fed information shocks significantly increase the likelihood of a rise in informed trading in the subsequent month. Specifically, based on our marginal effect estimations, a standard deviation contractionary shocks conveying positive news increases the probability of a rise in informed trading by more than 6%.

Interestingly, no equivalent effects are reported for the growth portfolio. This result testifies to the notion that widely documented valuation difficulties associated with value firms make the price non-synchronicity in their shares more dependent on the fresh economic news conveyed by FOMC announcements.

(Insert Table 7 about here)

The results in Table 8 complement our analysis by showing that the effects of Fed information shocks on the returns and crashes of the value portfolio (Models (3) and (4) respectively) become insignificant after introducing the change in informed trading as an additional explanatory variable. Moreover, the effects of the change in informed trading on these outcomes are as predicted. In particular, an increase in informed trading increases the returns of the value portfolio by almost 3% (Model (3)) and reduces the probability that the value portfolio will experience large crashes by more than 6% (based on our marginal effect estimations). Overall, this reported evidence is generally aligned with our original emphasis at the beginning of this paper on the changes in informed trading being the primary channel via which monetary surprises end up shaping the performance of value investing.

(Insert Table 8 about here)

7. Conclusion

The central contribution of this paper is in showing that information shocks by the Federal Reserve – i.e., monetary policy decisions that convey unanticipated information about the economy – have an integral role in shaping both the absolute and risk-adjusted returns from value investing. Building on the empirical approach developed by Jarociński and Karadi (2020), we identify positive (negative) Fed information shocks as the increases (decreases) in interest rates that are associated with a positive (negative) market reaction within the 30-minute window surrounding the Fed's announcement. In this context, a rise in interest rates is interpreted by equity investors as a reassuring signal of positive future economic developments, rather than a tightening measure that limits investment opportunities. In line with the theoretical model of (Dow, Goldstein, and Guembel 2017), we also posit that such reassuring economic signals incentivize a rise in the informed trading necessary to alleviate the mispricing of value companies.

We find that positive Fed information shocks create a suitable information environment for the realization of high returns from the value-based portfolio. In particular, such shocks predict a significant rise in the returns of the value portfolio in the subsequent month. Moreover, the positive risk-adjusted performance is largely realized in the aftermath of these shocks. These results hold when the Fama and French (1993) and the richer Fama and French (2015) specifications are used in assessing the risk-adjusted performance. Our analysis also supports the prediction that Fed's informational effect primarily operates through the changes in informed trading. In particular, adding the subsequent variation in price non-synchronicity to our models explains the leading effect of fed information shocks on the gains from value investing. Our results emphasize the consequential function of the Fed as an information producer. A direct implication of our results is that, despite their long-term orientation, value investors should give special attention to the economic signals conveyed by the Fed's announcements. As shown in our study, such signals have the potential of altering both the absolute and risk-adjusted performance of value portfolios, and hence shape the returns of one of the most established styles of stock investing.

References

Adra, S. 2021. "The Conventional and Informational Impacts of Monetary Policy on the IPO Market." *Economics Letters* 200. doi:10.1016/j.econlet.2021.109751.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen. 2013. "Value and Momentum Everywhere." *Journal of Finance* 68 (3): 929–985.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov. 2013. "Anomalies and Financial Distress." *Journal of Financial Economics* 108 (1): 139–159.

Baker, M, and J Wurgler. 2006. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance* 61: 1645–1680.

Barberis, Nicholas, and Andrei Shleifer. 2003. "Style Investing." *Journal of Financial Economics* 68: 161–199.

Barberis, Nicholas, and Richard H. Thaler. 2003. "A Survey of Behavioral Finance." *Handbook of the Economics of Finance* 1: 1053–1128.

Bernanke, Ben, and K. N. Kuttner. 2005. "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *Journal of Finance* 60: 1221–1257.

Breitenlechner, Max, Daniel Gründler, and Johann Scharler. 2021. "Unconventional Monetary Policy Announcements and Information Shocks in the US." *Journal of Macroecnomics* 67 (103283).

Chen, Nai-fu, and Feng Zhang. 1998. "Risk and Return of Value Stocks." *Journal of Business* 71 (4): 501–535.

Christopherson, Jon A., Wayne E. Ferson, and Debra A. Glassman. 1998. "Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance." *Review of Financial Studies* 11 (1): 111–142.

Cieslak, Anna, and Andreas Schrimpf. 2019. "Non-Monetary News in Central Bank Communication." *Journal of International Economics* 118: 293–315.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *American Economic Review* 105 (8): 2644–2678.

Damodaran, Aswath. 2012. *Investment Philosophies: Successful Strategies and the Investors Who Made Them Work*. John Wiley & Sons.

Daniel, Kent, David Hirshleifer, and Siew Hong Teoh. 2001. "Investor Psychology in Capital Markets: Evidence and Policy Implications." *Journal of Monetary Economics* 49 (1): 139–209.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98 (4): 703–738.

Dow, James, Itay Goldstein, and Alexander Guembel. 2017. "Incentives for Information Production in Markets Where Prices Affect Real Investment." *Journal of the European Economic Association* 15 (4): 877–909.

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on

Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56. doi:10.1016/0304-405X(93)90023-5.

Fama, Eugene, and Kenneth French. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116: 1–22.

Frazzini, Andrea, David Kabiller, and Lasse H. Pedersen. 2013. "Buffet's Alpha." *NBER Working Paper No. 19681*.

Gertler, Mark, and Peter Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics* 7 (1): 44–76.

Golubov, Andrey, and Theodosia Konstantinidi. 2019. "Where Is the Risk in Value? Evidence from AMarket-to-Book Decomposition." *Journal of Finance* 74 (6): 3135–3186.

Graham, B., and D.L. Dodd. 1934. *Security Selection*. New York, NY: McGraw-Hill.

Grossman, Sanford J., and Joseph E. Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets." *The American Economic Review* 70 (3): 393–408.

Habib, Ahsan, Mostafa Monzur Hasan, and Haiyan Jiang. 2018. "Stock Price Crash Risk: Review of the Empirical Literature." *Accounting & Finance* 58: 211–251.

Hattori, Masazumi, Andreas Schrimpf, and Vladyslav Sushko. 2016. "The Response of Tail Risk Perceptions to Unconventional Monetary Policy." *American Economic Journal: Macroeconomics* 8 (2): 111–136.

Hirshleifer, David. 2001. "Investor Psychology and Asset Pricing." *Journal of Finance* 56 (4): 1533–1597.

Hutton, Amy P., Alan J. Marcus, and Hassan Tehranian. 2009. "Opaque Financial Reports, R2, and Crash Risk." *Journal of Financial Economics* 94 (1): 67–86.

Jansen, Dennis W., and Anastasia Zervou. 2017. "The Time Varying Effect of Monetary Policy on Stock Returns." *Economics Letters* 160: 54–58.

Jarociński, Marek, and Peter Karadi. 2020. "Deconstructing Monetary Policy Surprises—The Role of Information Shocks." *American Economic Journal: Macroeconomics* 12 (2): 1–43.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–182.

Kodres, Laura, and Matthew Pritsker. 2002. "A Rational Expectations Model of Financial Contagion." *Journal of Finance* 57: 769–799.

Kok, U-Wen, Jason Ribando, and RIchard Sloan. 2016. "Facts about Formulaic Value Investing." *Financial Analysts Journal* 73 (2): 81–99.

Kumar, Alok. 2009. "Hard-to-Value Stocks, Behavioral Biases, and Informed Trading." *Journal of Financial and Quantitative Analysis* 44 (6): 1375–1401.

Kyle, A.S. 1985. "Continuous Auctions and Insider Trading." *Econometrica* 53: 1315–1335.

La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny. 1997. "Good News for Value Stocks: Further Evidence of Market Efficiency." *Journal of Finance* 52: 859–874.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny. 1994. “Contrarian Investment, Extrapolation, and Risk.” *Journal of Finance* 49 (5): 1541–1578.

Leibowitz, Martin L. 2005. “Alpha Hunters and Beta Grazers.” *Financial Analysts Journal* 61 (5): 117–126.

Miranda-Agrippino, Silvia, and Giovanni Ricco. 2021. “The Transmission of Monetary Policy Shocks.” *American Economic Journal: Macroeconomics* 13 (3): 74–107.

Nakamura, Emi, and Jón Steinsson. 2018. “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect.” *The Quarterly Journal of Economics* 133 (3): 1283–1330.

Pascal, Paul. 2019. “The Time-Varying Effect of Monetary Policy on Asset Prices.” *Review of Economics and Statistics*, 1–44.

Petkova, Ralitsa, and Lu Zhang. 2005. “Is Value Riskier than Growth?” *Journal of Financial Economics* 78: 187–202.

Piotroski, Joseph D., and Eric C. So. 2012. “Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach.” *Review of Financial Studies* 25 (9): 2841–2875.

Roll, Richard. 1988. “R2.” *Journal of Finance* 43: 541—566.

Romer, Christina D., and David H. Romer. 2000. “Federal Reserve Information and the Behavior of Interest Rates.” *American Economic Review* 90 (3): 429–457.

Shleifer, Andrei, and Robert W. Vishny. 1997. “The Limits of Arbitrage.” *The Journal of Finance* 52 (1): 35–55. doi:10.1111/j.1540-6261.1997.tb03807.x.

Thorbecke, Willem. 1997. “On Stock Market Returns and Monetary Policy.” *The Journal of Finance* 52 (2): 635–654. doi:10.1111/j.1540-6261.1997.tb04816.x.

Welch, Ivo, and Amit Goyal. 2007. “A Comprehensive Look at the Empirical Performance of Equity Premium Prediction.” *The Review of Financial Studies* 21 (4): 1455–1508.

Appendix 1: Local projection analysis

In this appendix, we apply the local projection analysis in a time series context, as developed by Jordà (2005), to track the effects of conventional and Fed information shocks, in addition to the remaining control variables, over a 12-month horizon. Specifically, we examine how the levels of the main variables at *t-1* influence the excess returns of the top value decile portfolio during the subsequent 12 months starting from *t* (the month covered primarily in our paper) and ending at *t+11*, inclusive. The overall evidence from Table A.1 suggests that the effect of Fed information shocks at *t-1* on the performance of the value portfolio is primarily captured in the subsequent calendar month *t*.

Table A.1: Local projection analysis

Dependent Variable	$Hi\_10_t - r_{f,t}$	$Hi\_10_{t+1} - r_{f,t+1}$	$Hi\_10_{t+2} - r_{f,t+2}$	$Hi\_10_{t+3} - r_{f,t+3}$	$Hi\_10_{t+4} - r_{f,t+4}$	$Hi\_10_{t+5} - r_{f,t+5}$	$Hi\_10_{t+6} - r_{f,t+6}$	$Hi\_10_{t+7} - r_{f,t+7}$	$Hi\_10_{t+8} - r_{f,t+8}$	$Hi\_10_{t+9} - r_{f,t+9}$	$Hi\_10_{t+10} - r_{f,t+10}$	$Hi\_10_{t+11} - r_{f,t+11}$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.715*	0.820**	1.010***	0.859**	1.009***	1.271***	1.167***	0.967***	1.212***	1.193***	1.212***	0.869**
	(0.376)	(0.395)	(0.393)	(0.394)	(0.363)	(0.377)	(0.389)	(0.369)	(0.358)	(0.374)	(0.368)	(0.377)
$\boldsymbol{\Delta Info_{t-1}}$	**17.805****	**-3.590**	**-12.939**	**2.581**	**9.666**	**6.592**	**-12.700**	**-20.987**	**13.212**	**20.602**	**-21.174**	**-1.2844**
	(9.093)	**(10.115)**	**(10.657)**	**(15.631)**	**(13.988)**	**(9.633)**	**(10.049)**	**(20.044)**	**(20.783)**	**(17.824)**	**(21.523)**	**(28.146)**
$\boldsymbol{\Delta Regular_{t-1}}$	**-0.328**	**1.038**	**5.030**	**-6.273**	**7.067**	**2.362**	**0.554**	**-9.198**	**3.319**	**7.392**	**-6.392**	**-4.025**
	(4.093)	**(5.149)**	**(6.746)**	**(6.528)**	**(6.006)**	**(6.158)**	**(6.742)**	**(5.747)**	**(6.187)**	**(6.141)**	**(5.109)**	**(6.781)**
$R_{M,t-1} - R_{f,t-1}$	0.153	0.355**	-0.004	0.032	0.101	0.145	-0.128	0.016	-0.128	0.028	-0.342*	-0.018
	(0.179)	(0.178)	(0.217)	(0.175)	(0.205)	(0.188)	(0.199)	(0.189)	(0.209)	(0.198)	(0.192)	(0.224)
SMB_{t-1}	-0.065	0.168	-0.232*	0.021	-0.211	-0.151	-0.078	0.052	-0.035	-0.006	-0.020	0.037
	(0.146)	(0.128)	(0.142)	(0.130)	(0.143)	(0.140)	(0.144)	(0.135)	(0.145)	(0.141)	(0.138)	(0.147)
CMA_{t-1}	0.207	0.181	-0.220	0.036	0.154	0.121	0.124	0.169	-0.140	-0.026	-0.389*	0.077
	(0.202)	(0.198)	(0.207)	(0.180)	(0.218)	(0.184)	(0.212)	(0.229)	(0.226)	(0.213)	(0.212)	(0.217)
RMW_{t-1}	-0.171	0.067	-0.074	0.053	-0.167	-0.376	-0.181	0.024	0.032	-0.056	-0.074	0.127
	(0.154)	(0.167)	(0.149)	(0.142)	(0.169)	(0.161)	(0.172)	(0.153)	(0.158)	(0.181)	(0.160)	(0.166)
$Hi\_10_{t-1} - r_{f,t-1}$	0.094	-0.273**	0.053	0.058	-0.078	-0.303***	0.011	0.052	0.030	-0.096	0.243**	0.126
	(0.131)	(0.136)	(0.153)	(0.125)	(0.140)	(0.116)	(0.147)	(0.123)	(0.154)	(0.139)	(0.121)	(0.142)
N	321	320	319	318	317	316	315	314	313	312	311	310
R-Squared	0.03	0.01	0.01	0.01	0.01	0.04	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table applies the Jordà (2005) local projection analysis to track the effects of the variable at month *t-1* on the subsequent 12 months, specifically from month *t* to month *t+11*, inclusive. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 1: Description of the variables

Acronym	Description	Source
$\Delta Info$	The monthly change in Fed Information Shocks. These shocks are defined as the 30-minute changes in interest rates that take place around FOMC announcements and that are positively correlated with stock market returns.	Jarociński and Karadi (2020)
$\Delta Regular$	The monthly change in Conventional Monetary Shocks. These shocks are defined as the 30-minute changes in interest rates that take place around FOMC announcements and that are negatively correlated with stock market returns.	Jarociński and Karadi (2020)
r_M	The returns of the value-weighted portfolio of the US-incorporated CRSP companies that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11.	Professor Kenneth French's website
SMB	The average return on the three groups of large stocks is subtracted from the average return on the three groups of small stocks. The resulting estimates are then averaged to produce SMB.	Professor Kenneth French's website
CMA	The average return on two conservative investment portfolios (the biggest and the smallest in size) minus the average return on the two aggressive investment portfolios (the biggest and the smallest in size).	Professor Kenneth French's website
RMW	The average return on the two robust operating profitability portfolios (the biggest and the smallest in size) minus the average return on the two weak operating profitability portfolios (the biggest and the smallest in size).	Professor Kenneth French's website
Hi_10	The return on the portfolio in the highest book-to-market decile based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
Hi_20	The return on the portfolio in the highest book-to-market quantile based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
Hi_30	The return on the portfolio in the top 30% of book-to-market valuations based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
Lo_10	The return on the portfolio in the lowest book-to-market decile based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
Lo_20	The return on the portfolio in the lowest book-to-market quantile based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
Lo_30	The return on the portfolio in the bottom 30% of book-to-market valuations based on sorts conducted on all NYSE, AMEX, and NASDAQ stock. The book value is based on data available in June while the market value is based on data available in December.	Professor Kenneth French's website
r_f	The one-month rate of return on U.S. Treasury Bills.	Professor Kenneth French's website (from Ibbotson Associates)
$GrowthInfoRise$	Dummy = 1 if the level of non-synchronized trading in the growth portfolio Lo_10 increased by more than 1%, and 0 otherwise.	Professor Kenneth French's website + Authors' Estimations
$ValueInfoRise$	Dummy = 1 if the level of non-synchronized trading in the value portfolio Hi_10 increased by more than 1%, and 0 otherwise.	Professor Kenneth French's website + Authors' Estimations

Table 2: Descriptive Statistics

Variable	Mean	Median	Max	Min	SD
Hi_10	1.15	1.61	24.93	-23.79	6.26
Hi_20	1.11	1.77	18.43	-17.35	5.25
Hi_30	1.04	1.50	17.14	-21.38	4.94
Lo_10	0.86	0.86	15.67	-15.47	4.71
Lo_20	0.94	1.26	11.34	-17.68	4.20
Lo_30	0.89	1.09	14.15	-15.78	4.33
$\Delta Info$	0.00	0.00	0.26	-0.26	0.03
$\Delta Regular$	0.00	0.00	0.30	-0.37	0.07
r_M	0.88	1.37	11.35	-17.15	4.28
SMB	0.19	0.11	18.08	-14.89	3.08
CMA	0.25	0.04	9.56	-6.86	2.10
RMW	0.37	0.41	13.38	-18.48	2.71
r_f	0.23	0.24	0.69	0.00	0.19

Note: For each variable used in this study, this table reports the mean, median, maximum and minimum levels, in addition to the standard deviation.

Table 3: Predicting the excess returns of value and growth portfolios

Panel A: Benchmark Results						
Dependent Variable	$Lo\_10_t - r_{f,t}$	$Lo\_20_t - r_{f,t}$	$Lo\_30_t - r_{f,t}$	$Hi\_30_t - r_{f,t}$	$Hi\_20_t - r_{f,t}$	$Hi\_10_t - r_{f,t}$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.790*** (0.305)	0.752*** (0.270)	0.792*** (0.281)	0.757** (0.322)	0.764** (0.336)	0.779** (0.386)
$R_{M,t-1} - R_{f,t-1}$	-0.253 (0.227)	0.013 (0.198)	-0.177 (0.352)	-0.059 (0.260)	0.158 (0.200)	0.147 (0.198)
SMB_{t-1}	-0.067 (0.103)	-0.023 (0.098)	-0.058 (0.095)	-0.080 (0.115)	-0.011 (0.119)	-0.054 (0.145)
CMA_{t-1}	-0.114 (0.205)	-0.066 (0.145)	-0.115 (0.183)	-0.074 (0.205)	0.077 (0.183)	0.144 (0.220)
RMW_{t-1}	-0.221* (0.133)	-0.135 (0.134)	-0.201 (0.125)	-0.120 (0.131)	-0.094 (0.135)	-0.160 (0.148)
N	322	322	322	322	322	322
Lagged Portfolio Excess Return	YES	YES	YES	YES	YES	YES
R-Squared	0.02	0.01	0.02	0.03	0.03	0.04
Adjusted R-Squared	0.01	0.01	0.01	0.02	0.01	0.02
Panel B: The Effects of Central Bank Shocks						
Dependent Variable	$Lo\_10_t - r_{f,t}$	$Lo\_20_t - r_{f,t}$	$Lo\_30_t - r_{f,t}$	$Hi\_30_t - r_{f,t}$	$Hi\_20_t - r_{f,t}$	$Hi\_10_t - r_{f,t}$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.742*** (0.266)	0.707*** (0.254)	0.742*** (0.266)	0.721 (0.324)	0.744** (0.329)	0.715* (0.376)
$\boldsymbol{\Delta Info_{t-1}}$	**1.267** **(7.417)**	**4.066** **(0.068)**	**1.267** **(7.417)**	**9.728** **(7.752)**	**13.625*** **(8.480)**	**17.805**** **(9.093)**
$\boldsymbol{\Delta Regular_{t-1}}$	**1.076** **(2.372)**	**-0.336** **(2.550)**	**1.076** **(2.372)**	**-0.481** **(3.091)**	**0.629** **(3.199)**	**-0.328** **(4.093)**
$R_{M,t-1} - R_{f,t-1}$	-0.163 (0.288)	0.006 (0.180)	-0.163 (0.288)	-0.093 (0.234)	0.096 (0.200)	0.153 (0.179)
SMB_{t-1}	-0.068 (0.089)	-0.034 (0.102)	-0.068 (0.089)	-0.107 (0.108)	-0.053 (0.116)	-0.065 (0.146)
CMA_{t-1}	-0.094 (0.157)	-0.030 (0.148)	-0.094 (0.157)	-0.032 (0.188)	0.111 (0.179)	0.207 (0.202)
RMW_{t-1}	-0.201* (0.114)	-0.138 (0.127)	-0.201* (0.114)	-0.127 (0.131)	-0.107 (0.135)	-0.171 (0.154)
N	321	321	321	321	321	321
Lagged Portfolio Excess Return	YES	YES	YES	YES	YES	YES
R-Squared	0.02	0.01	0.02	0.04	0.03	0.05
Adjusted R-Squared	0.01	0.01	0.01	0.02	0.01	0.03

Note: This table presents a set of models predicting the excess returns of value and growth portfolios. The portfolios are defined in Table 1. Panel A presents benchmark results that include the one-month lagged excess returns of each portfolio and the Fama French (2015) factors as regressors. Panel B adds the Fed information and regular shocks as additional regressors. Heteroskedasticity-robust standard errors (Newey-West) are reported within parentheses. Our sample covers 323 months between February 1990 and December 2016. When one-month lags are used on Panel A, the number of observations decreases to 322 as the first observation in the sample is dropped. The calculation of the information and regular shocks in the form of monthly differences and including them at the one-month lag in Panel B reduces the sample to 321 observations as the first two observations in the sample are dropped. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 4: Predicting the crashes in the returns of value and growth portfolios

Panel A: Benchmark Results						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$Crash(Lo\_10_t)$	$Crash(Lo\_20_t)$	$Crash(Lo\_30_t)$	$Crash(Hi\_30_t)$	$Crash(Hi\_20_t)$	$Crash(Hi\_10_t)$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.355*** (0.223)	-2.208*** (0.201)	-2.109*** (0.200)	-2.296*** (0.211)	-2.297*** (0.211)	-2.288*** (0.214)
$R_{M,t-1} - R_{f,t-1}$	-0.235* (0.133)	-0.071 (0.173)	-0.227* (0.124)	0.115 (0.118)	0.025 (0.098)	0.027 (0.095)
SMB_{t-1}	-0.043 (0.071)	0.010 (0.069)	0.003 (0.066)	0.028 (0.074)	0.044 (0.071)	0.094 (0.076)
CMA_{t-1}	0.165 (0.116)	-0.042 (0.102)	0.098 (0.107)	0.111 (0.116)	0.165 (0.106)	0.037 (0.109)
RMW_{t-1}	0.045 (0.081)	0.062 (0.092)	0.019 (0.077)	0.052 (0.089)	0.015 (0.080)	0.032 (0.084)
N	322	322	322	322	322	322
Lagged Portfolio Return	YES	YES	YES	YES	YES	YES
Mc Fadden R-Squared	0.05	0.04	0.03	0.09	0.08	0.09
Panel B: The Effects of Central Bank Shocks						
Dependent Variable	$Crash(Lo\_10_t)$	$Crash(Lo\_20_t)$	$Crash(Lo\_30_t)$	$Crash(Hi\_30_t)$	$Crash(Hi\_20_t)$	$Crash(Hi\_10_t)$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.386*** (0.230)	-2.205*** (0.203)	-2.372*** (0.238)	-2.290*** (0.213)	-2.367*** (0.219)	-2.317*** (0.219)
$\boldsymbol{\Delta Info_{t-1}}$	**-7.795** **(5.644)**	**-7.414** **(5.703)**	**-7.0050** **(5.585)**	**-4.509** **(5.868)**	**-9.389*** **(5.782)**	**-14.217**** **(6.772)**
$\boldsymbol{\Delta Regular_{t-1}}$	**2.101** **(2.859)**	**-0.339** **(2.855)**	**0.758** **(2.968)**	**-1.406** **(2.950)**	**-1.7890** **(3.091)**	**-1.981** **(2.981)**
$R_{M,t-1} - R_{f,t-1}$	-0.246* (0.135)	-0.035 (0.178)	-0.256 (0.251)	0.118 (0.118)	0.075 (0.102)	0.030476 (0.097)
SMB_{t-1}	-0.054 (0.072)	0.011 (0.071)	0.007 (0.075)	0.031 (0.075)	0.073 (0.074)	0.096 (0.079)
CMA_{t-1}	0.158 (0.117)	-0.051 (0.104)	0.104 (0.110)	0.106 (0.116)	0.156 (0.109)	0.014 (0.112)
RMW_{t-1}	0.052 (0.082)	0.080 (0.094)	0.048 (0.083)	0.058 (0.089)	0.036 (0.082)	0.044 (0.086)
N	321	321	321	321	321	321
Lagged Portfolio Excess Return	YES	YES	YES	YES	YES	YES
Mc Fadden R-Squared	0.06	0.05	0.07	0.08	0.08	0.12

Note: This table presents a set of Logit models predicting the crashes in value and growth portfolios. In each Logit model, the dependent variable is assigned the value of 1 if the portfolio's returns are in the bottom decile, and 0 otherwise. The portfolios are defined in Table 1. Panel A presents benchmark results that include the one-month lagged excess returns of each portfolio and the Fama French (2015) factors as regressors. Panel B adds the Fed information and regular shocks as additional regressors. Heteroskedasticity-robust standard errors are reported within parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 5: The risk-adjusted performance of value and growth portfolios

Dependent Variable	$Lo\_10_t - r_{f,t}$	$Lo\_20_t - r_{f,t}$	$Lo\_30_t - r_{f,t}$	$Hi\_30_t - r_{f,t}$	$Hi\_20_t - r_{f,t}$	$Hi\_10_t - r_{f,t}$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	-0.038 (0.200)	0.103 (0.099)	0.021 (0.058)	0.151 (0.188)	0.201 (0.204)	0.120 (0.242)
$\boldsymbol{\Delta Info_{t-1}}$	**0.948** **(3.886)**	**1.231** **(1.585)**	**-1.025** **(1.700)**	**5.503*** **(3.155)**	**9.180***** **(3.497)**	**12.301***** **(3.936)**
$\boldsymbol{\Delta Regular_{t-1}}$	**0.579** **(1.278)**	**-1.030** **(1.224)**	**0.098** **(0.507)**	**-0.690** **(1.828)**	**0.301** **(2.014)**	**-0.321** **(2.657)**
$r_{M,t} - r_{f,t}$	1.045*** (0.032)	0.933*** (0.031)	1.005*** (0.017)	0.974*** (0.071)	1.014*** (0.066)	1.131*** (0.081)
SMB_t	-0.129*** (0.039)	-0.029*** (0.077)	-0.097*** (0.017)	0.211*** (0.072)	0.243** (0.992)	0.418*** (0.125)
N	321	321	321	321	321	321
R-Squared	0.88	0.90	0.96	0.78	0.76	0.71
Adjusted R-Squared	0.88	0.90	0.96	0.78	0.76	0.71

Note: This table presents a set of models assessing the risk-adjusted performance of value and growth portfolios. The portfolios are defined in Table 1. In addition to the FF (1993) factors (excluding HML), these models control for the Fed information and regular shocks as additional regressors in estimating the conditional alphas. Heteroskedasticity-robust standard errors (Newey-West) are reported within parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 6: The risk-adjusted performance of value and growth portfolios based on FF (2015)

Dependent Variable	$Lo\_10_t - r_{f,t}$	$Lo\_20_t - r_{f,t}$	$Lo\_30_t - r_{f,t}$	$Hi\_30_t - r_{f,t}$	$Hi\_20_t - r_{f,t}$	$Hi\_10_t - r_{f,t}$
Variable\Model (.)	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.150 (0.103)	-0.104 (0.073)	0.085 (0.053)	-0.187 (0.127)	-0.111 (0.137)	-0.239 (0.190)
$\boldsymbol{\Delta Info_{t-1}}$	**3.272** **(3.896)**	**0.715** **(1.385)**	**0.202** **(1.722)**	**2.736** **(3.000)**	**6.519*** **(3.444)**	**8.909**** **(3.922)**
$\boldsymbol{\Delta Regular_{t-1}}$	**-0.458** **(1.068)**	**-0.425** **(1.066)**	**-0.371** **(0.415)**	**0.802** **(1.554)**	**1.706** **(1.826)**	**1.3868** **(2.423)**
$r_{M,t} - r_{f,t}$	0.956*** (0.027)	1.019*** (0.023)	0.971*** (0.018)	1.126*** (0.052)	1.155*** (0.044)	1.296*** (0.072)
SMB_t	-0.121*** (0.031)	0.041 (0.045)	-0.078*** (0.020)	0.250*** (0.053)	0.275*** (0.072)	0.443*** (0.088)
CMA_t	-0.480*** (0.051)	0.221*** (0.049)	-0.229*** (0.033)	0.650*** (0.083)	0.616*** (0.084)	0.760*** (0.106)
RMW_t	-0.003 (0.048)	0.210*** (0.049)	0.042 (0.031)	0.147* (0.085)	0.125 (0.118)	0.111 (0.138)
N	321	321	321	321	321	321
R-Squared	0.92	0.92	0.97	0.86	0.82	0.77
Adjusted R-Squared	0.91	0.92	0.97	0.85	0.81	0.77

Note: This table presents a set of models assessing the risk-adjusted performance of value and growth portfolios. The portfolios are defined in Table 1. In addition to the FF(2015) factors (excluding HML), these models control for the Fed information and regular shocks as additional regressors in estimating the conditional alphas. Heteroskedasticity-robust standard errors (Newey-West) are reported within parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 7: Predicting the rise in price non-synchronicity

Dependent Variable	$GrowthInfoRise_t$	$ValueInfoRise_t$
Variable\Model (.)	(1)	(2)
Intercept	-0.370***	-0.025
	(0.125)	(0.124)
$\boldsymbol{\Delta Info_{t-1}}$	**5.352**	**23.660****
	(4.798)	**(11.322)**
$\boldsymbol{\Delta Regular_{t-1}}$	**1.983**	**-3.228**
	(2.386)	**(2.525)**
$R_{M,t-1} - R_{f,t-1}$	0.006	0.005
	(0.087)	(0.057)
SMB_{t-1}	0.088**	0.049
	(0.044)	(0.046)
CMA_{t-1}	0.023	-0.007
	(0.072)	(0.066)
RMW_{t-1}	0.027	0.009
	(0.055)	(0.054)
Lagged Portfolio Return	YES	YES
N	321	321
Mc Fadden R-Squared	0.01	0.02

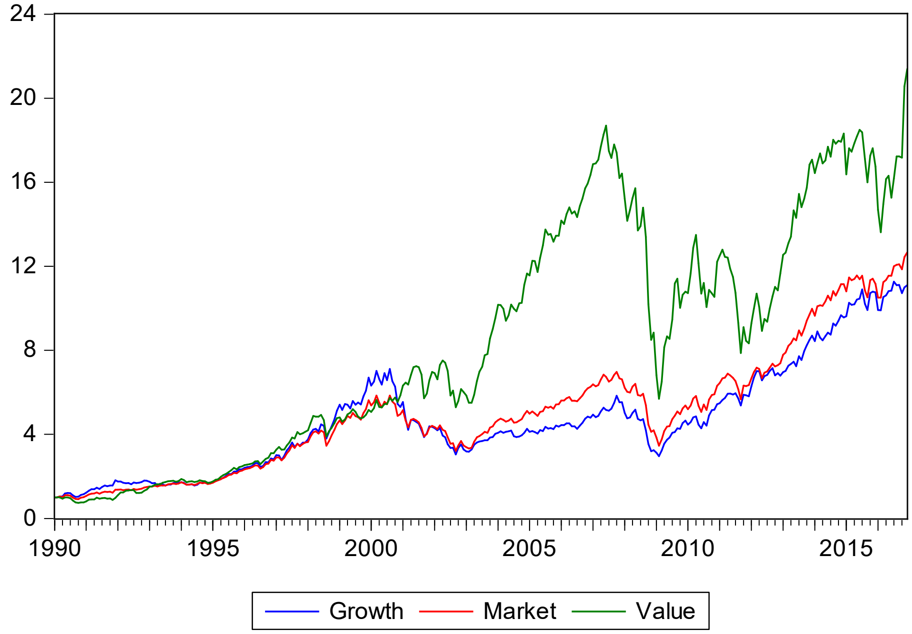
Note: This table presents two logit models predicting the rise in non-synchronized trading by more than 1% in growth stocks ($GrowthInfoRise$ for Lo_10) and value stocks ($ValueInfoRise$ for Hi_10), respectively. For each calendar month, we run a CAPM model using daily data of roughly 22 trading days for both growth and the value portfolios. We treat the part of the variation in excess returns that is not explained by the CAPM model as a proxy for the level of price informativeness in each month. To avoid the potential impact of noisiness on our estimates, we assign for each month a dummy variable, depending on whether the growth and value portfolio experienced a rise in informed trading. For the growth portfolio, we construct the variable *GrowthInfoRise* which is assigned the value of 1 if the level of non-synchronized trading in the growth portfolio increases by more than 1% relative to the prior month, and 0 otherwise. Equivalently, *ValueInfoRise* is assigned the value of 1 if the level of non-synchronized trading in the value portfolio increases by more than 1% relative to the prior month, and 0 otherwise. Heteroskedasticity-robust standard errors are reported within parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Table 8: The effect of increases in non-synchronized trading on portfolio returns and crashes

Dependent Variable	$Lo\_10_t - r_{f,t}$	$Crash(Lo\_10_t)$	$Hi\_10_t - r_{f,t}$	$Crash(Hi\_10_t)$
Variable\Model (.)	(1)	(2)	(3)	(4)
Intercept	0.520 (0.338)	-2.581*** (0.303)	-0.868* (0.529)	-2.190*** (0.307)
$\boldsymbol{GrowthInfoRise_t}$	**0.710 (0.576)**	**0.498 (0.388)**		
$\boldsymbol{ValueInfoRise_t}$			**2.931*** (0.712)**	**-0.853** (0.437)**
$\boldsymbol{\Delta Info_{t-1}}$	**2.611 (15.518)**	**-8.183 (6.264)**	**11.733 (16.162)**	**-11.127 (7.040)**
$\boldsymbol{\Delta Regular_{t-1}}$	**3.224 (5.478)**	**0.883 (4.472)**	**1.473 (7.057)**	**-6.425* (3.764)**
$R_{M,t-1} - R_{f,t-1}$	-0.227 (0.197)	-0.251* (0.136)	0.120 (0.173)	0.037 (0.100)
SMB_{t-1}	-0.079 (0.093)	-0.068 (0.073)	-0.090 (0.134)	0.103 (0.079)
CMA_{t-1}	-0.135 (0.195)	0.176 (0.117)	0.148 (0.195)	0.058 (0.110)
RMW_{t-1}	-0.222* (0.120)	0.054 (0.081)	-0.179 (0.153)	0.043 (0.083)
N	321	321	321	321
R-Squared (Mc Fadden)	0.03	0.06	0.11	0.14

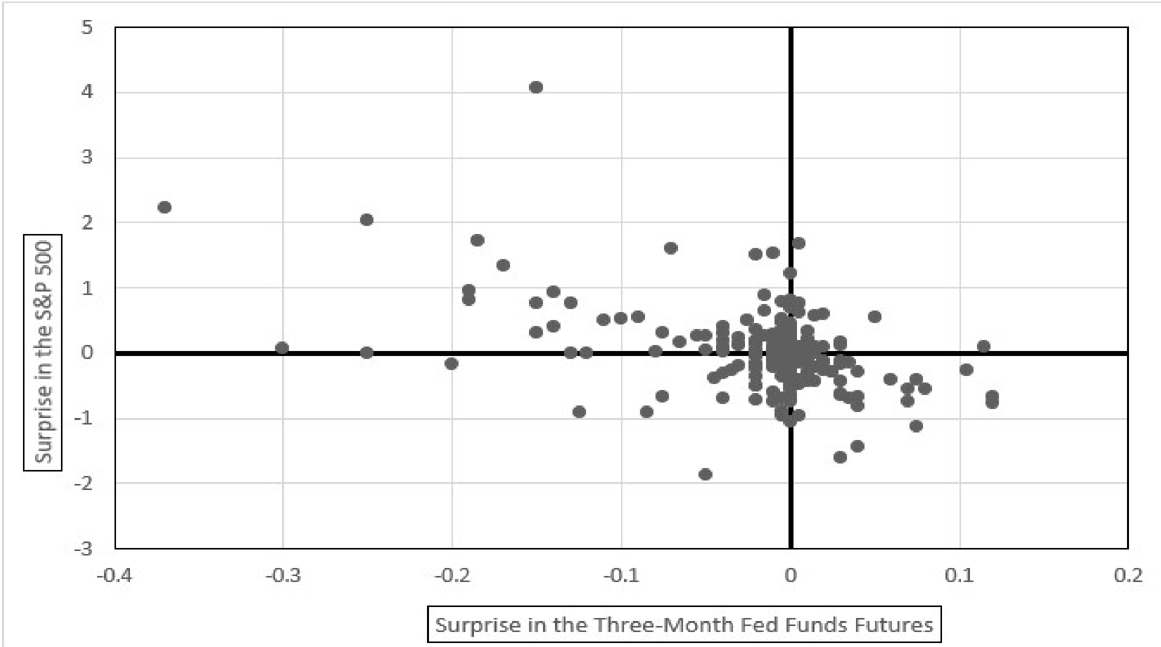
Note: This table presents a set of models depicting how the growth in non-synchronized trading influences the returns and crashes of the growth and value portfolios. Models (1) and (3) explain the returns of the growth (Lo_10) and value portfolio (Hi_10), respectively. Models (2) and (4) are logit specifications predicting the likelihood of crashes in the growth and value portfolio, respectively. For each calendar month, we run a CAPM model using daily data of roughly 22 trading days for both growth and the value portfolios. We treat the part of the variation in excess returns that is not explained by the CAPM model as a proxy for the level of price informativeness in each month. To avoid the potential impact of noisiness on our estimates, we assign for each month a dummy variable, depending on whether the growth and value portfolio experienced a rise in informed trading. For the growth portfolio, we construct the variable *GrowthInfoRise* which is assigned the value of 1 if the level of non-synchronized trading in the growth portfolio increases by more than 1% relative to the prior month, and 0 otherwise. Equivalently, *ValueInfoRise* is assigned the value of 1 if the level of non-synchronized trading in the value portfolio increases by more than 1% relative to the prior month, and 0 otherwise. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Figure 1: The cumulative gains from value, growth, and market portfolios



Note: This graph presents the cumulative dollar gains until December 2016 of 1 U.S. dollar invested in value, growth, and market portfolios in January 1990.

Figure 2: Interest rates and S&P 500 around FOMC meetings



Note: This scatterplot represents the thirty-minute changes in the Fed funds futures and the S&P 500 in the 30-minute window surrounding each FOMC meeting. Each dot represents a separate FOMC meeting between February 1990 and December 2016.