Volume dynamics around macroeconomic announcements

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Abstract

This paper investigates volume dynamics in the financial market around macroeconomic announcements. Volumes in the stock market are abnormally low in anticipation of FOMC announcements compared to their past monthly trend. In the cross section, assets with higher systematic risks exhibit greater volume changes. This negative pre-announcement risk-volume relation is reversed after announcements. I attribute the cross-sectional relation between volume and systematic risk to a theory where macroeconomic news resolves information asymmetries. Consistent with this explanation, I find price impact increases in anticipation of FOMC announcements and decreases afterwards, especially for assets with high systematic risks. I find little evidence that volume declines in anticipation of other types of macroeconomic announcements.

Keywords: Macroeconomic news, trading volume, liquidity, information asymmetry

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http://.

1 Introduction

On the day ahead of U.S. Federal Reserve's August policy meeting in 2001, an article in the Wall Street Journal reads *"Trading is on hold as investors await news from Fed meeting"*. The phenomenon that treasury markets are particularly quiet on days prior to scheduled macroeconomic announcements is called the *"calm before the storm"* effect by Jones, Lamont and Lumsdaine (1998). Does this effect also exist in the stock market? What prevents investors trading in anticipation of announcements? To answer these questions, I examine the volume dynamics in the stock market around major macroeconomic announcements.

Recent studies find that financial markets perform surprisingly well on days with macroeconomic announcements such as the Federal Operation Market Committee interest rate decision (hereafter, FOMC), the release of unemployment rate and Purchasing Managers' Index (hereafter, PMI) and so on [1]. Nevertheless, any type of information shock, including those triggered by macroeconomic announcements, has to be incorporated into prices through trading. Therefore, the investigation of volume dynamics is of natural importance to understand the financial market around macroeconomic announcements.

The contribution of this paper is twofold. First, I document the volume dynamics in the stock market around macroeconomic announcements, with an emphasis on the cross sectional perspective. In addition, I examine the mechanism behind the unexpected volume changes around scheduled macroeconomic announcements.

The investigation of volume dynamics around macroeconomic announcements is a challenging task. New information disseminates much faster than it used to be and previous studies show that macroeconomic announcements are absorbed by the financial market within one day (Savor and Wilson (2014), Lucca and Moench (2015), Bernile, Hu and Tang (2016), Ai and Bansal (2018)). For this reason, it is crucial to study volume dynamics separately for the pre-

[1] From 1993–2018, the average return of the S&P 500 index is about 3 basis points per day, with a volatility of 118 basis points. After subtracting the one-month treasury bill rate, this is equivalent to an annualized Sharpe ratio of less than 0.5. In contrast, during the thirty days with macroeconomic announcements each year, the average daily return of the S&P 500 index is about 11 basis points and its annualized Sharpe ratio is 1.84. Meanwhile, stock market betas perform surprisingly well on macroeconomic announcement days to predict stock excess returns in the cross section (see Savor and Wilson (2014) for more discussions). Traditional risk measures such as realized volatility or VIX fail to explain these anomalies

and post-announcement hours within a narrow trading window. To this end, I obtain intraday tick-by-tick trading volumes for all securities that are components of S&P 500 index after 1993 [2].

In my empirical analysis, I want to work with stationary data but volume series are usually nonstationary. For this reason, I follow Campbell, Grossman and Wang (1993) and construct a stationary time series, *abnormal turnover*, to investigate the volume dynamics around macroeconomic announcements. Abnormal turnover is essentially the monthly-detrended log turnover and it is also easy to interpret. One unit of abnormal turnover in period t indicates that the turnover of an asset increases by 100% in that period comparing to its average level over the previous month.

Having established a stationary volume measure, I then investigate the abnormal turnover in the stock market around major macroeconomic announcements. Figure 6 illustrates the average abnormal turnover of SPDR S&P500 ETF (i.e. SPDR) by 5-minutes intervals around scheduled FOMC announcements since September 1994. Consistent with the “calm before the storm” effect, the turnover of SPDR drops by over 12% in anticipation of FOMC announcements relative to their monthly average. At the announcement time, the turnover of SPDR skyrockets by about 150%, implies an intensive increase in trading activities. The market continues to be abnormally active on the day after FOMC announcements.

After showing the volume dynamics in SPDR around FOMC announcements, I find this phenomenon is widespread in individual stocks as well. In Jones, Lamont and Lumsdaine (1998), the authors find that the magnitude of the “calm before the storm” effect is monotonically increasing with the maturity of the bond. Likewise, I find that individual abnormal turnovers are monotonically increasing with the stocks’ exposure to the macroeconomic risk. To study the volume dynamics in a cross sectional perspective, I investigate the abnormal turnover of each stock in the 24 hours before (henceforth, *PreFOMC* days) and after (henceforth, *PostFOMC* days) scheduled FOMC announcements. I then divide individual stocks into decile groups according

[2] The reason I only use S&P 500 stocks in the empirical analysis is due to the limitation of computational power. It is not feasible to obtain, store and process the intraday trades data for all listed securities for such a long time span.

to their market betas[3] to illustrate the relation between market beta and abnormal turnover. I define the abnormal turnover of each portfolio as the value-weighted average of individual abnormal turnovers. The middle line in Figure 4 shows that the average abnormal turnover is essentially zero on *NonFOMC* days and do not vary with the market beta. In contrast, the bottom and top lines indicate that turnovers of individual stocks on average decline by about 2.06% before FOMC announcements and increase by 10.29% afterwards, comparing with their past monthly average.

In the cross section, the change in turnover is more profound for stocks with a greater exposure to the macroeconomic risk. On *PreFOMC* days, a stock with a market beta of 0.5 unit are traded 1% less than its past monthly average. In comparison, a stock with a market beta of 1.5 are traded about 3% less than its past monthly average. On *PostFOMC* days, the correlation between the abnormal turnover and the market beta turns into a positive one, as is showed by the top line in Figure 4.

Volumes and volatilities usually move in tandem. Therefore, one natural interpretation of the volume dynamics around FOMC announcements might be related to an exogenous change in macroeconomic risk. As a matter of fact, I find that the absolute return of the SPDR decreases by about 28% before FOMC announcements and increases by 16% afterwards, comparing to its past monthly average level. Additionally, I find that the increase in volatility after announcements is mainly induced by volume changes. However, the pre-announcement decrease in volatility is not induced by volumes, which might imply an exogenous reduction in aggregate risk or uncertainty before macroeconomic announcements (Ai and Bansal (2018), Hu et al. (2019)).

To interpret the volume dynamics in the stock market around FOMC announcements, I develop a rational expectation equilibrium model with *discretionary liquidity traders*[4]. Inspired by the fact that volatility has already declined before FOMC announcements, I assume that

[3]For a given trading day d, individual market betas are estimated from one-year rolling CAPM regressions up to day $d-1$.

[4]Trades in financial markets are widely accepted to be motivated by either information or liquidity. Informed traders are arbitrageurs who trade based on private information, while liquidity traders trade for non-profit reasons that arise outside the financial market. Although most models that involve liquidity traders assume them to arrive at the market randomly, Admati and Pfleiderer (1988) demonstrate that at least some liquidity traders, can choose the timing of their transaction strategically, subject to the constraint of trading a particular number of shares within a given period of time. Liquidity traders that can strategically choose the timing of their transaction is usually referred to as *discretionary liquidity traders*.

a signal about the future economic state arrives to a certain group of investors before being announced by FOMC publicly. The theoretical model is similar to Admati and Pfleiderer (1988) and Kim and Verrecchia (1991) but differs in two explicit assumptions: 1. the role and timing of public news are different; 2. individual stocks have diverse exposures to public news.

The model's first result is that volumes in the financial market decline before scheduled macroeconomic announcements and increase afterwards. In anticipation of macroeconomic announcements, information asymmetries temporarily increase either due to informational leaks (Bernile, Hu and Tang (2016), Ai and Bansal (2018), Cieslak, Morse and Vissing-Jorgensen (2018), Vissing-Jorgensen (2020)) or superior information-processing capabilities of sophisticated investors (Kim and Verrecchia (1994), Engelberg, Reed and Ringgenberg (2012), Di Maggio and Pagano (2018)). Regardless of reasons behind the rise of information asymmetries, outcomes are the same: a certain group of investors are informed about the public signal before announcements, while others do not. As a consequence, discretionary liquidity traders who are informationally disadvantaged prefer to hold their exogenous demands until macroeconomic news are announced. Given that the number of discretionary liquidity traders is massive, their behavior can dominantly determine the volume dynamic in financial markets around macroeconomic announcements.

In the cross section, the model predicts that stocks with higher systematic risks have greater volume changes around macroeconomic news, than traders who invest in stocks of lower systematic risks. The reason is that the information disadvantage before macroeconomic announcements is higher for the former group of stocks.

Last but not least, because discretionary liquidity tradings are clustered after announcements, the model predicts that price impacts increase before macroeconomic announcements and decrease afterwards. In the cross section, stocks with higher systematic risks should experience deeper decline in price impact than stocks with lower systematic risks.

For the most part of analysis, I study the volume dynamics around scheduled FOMC announcements rather than other types of macroeconomic announcements for two reasons. Firstly, previous studies find that FOMC announcements are associated with a much higher announcement premium than other types of macroeconomic announcements (Savor and Wilson (2014)).

This implies that FOMC announcements contain information that is more relevant to investors in the stock market. Secondly, FOMC consist of several committee members and therefore the possibility of information leakage is higher (Vissing-Jorgensen (2020)). I compare trading activities in the 24 hours before FOMC announcements (*PreFOMC* days), in the 24 hours after FOMC announcements (*PostFOMC* days) and on non-event days (*NonFOMC* days) using panel regressions from 1993 to 2018. The analysis generates three main results: (1) Turnovers of individual stocks are 1.4%–3.3% lower on *PreFOMC* days and 7.7%–9.7% higher on *PostFOMC* days, comparing to their past monthly average. (2) Abnormal turnovers around FOMC announcements are larger in magnitude for stocks with higher market betas. (3) Price impact on average increases by about 13% on *PreFOMC* days, while it declines by 23% on *PostFOMC* days. In the cross section, changes in the information environment are more concentrated among assets with high systematic risks.

These findings are consistent with predictions of the model with private information and discretionary liquidity traders. The second and third empirical findings are novel, whereas the first finding significantly extend previous results.

Having documented the trading activities in the stock market around FOMC announcements, I extend the analysis to another two types of macroeconomic announcements—the release of NonFarm Payroll employment by Bureau of Labor Statistics and the release of Purchasing Managers' Index by Institute for Supply Management. I find little evidence that the stock market exhibits a "calm before the storm" volume pattern before these types of macroeconomic announcements.

2 Related literature

This paper contributes to the large strand of literature that investigates the price formation around economic news. Early studies mostly investigate the price formation and liquidities around macroeconomic news in the US treasury market (Fleming and Remolona (1999), Balduzzi, Elton and Green (2001), Green (2004), Jiang, Lo and Verdelhan (2011)) and the currency market (Evans and Lyons (2008)).

Recent literature starts to examine the relation between the equity premium and macroeconomic news. One strand of literature investigates if macroeconomic news affect stock prices by resolving uncertainties. Cieslak, Morse and Vissing-Jorgensen (2018) find that in the period from 1994 to 2016, the equity premium is earned entirely in even weeks between FOMC meeting cycles. They attribute this high realized even-week stock returns to the resolution of uncertainties resulting from the informal communication between the Fed and the public media. Hu et al. (2019) find a gradual build-up in VIX over a window of up to six business days prior to FOMC announcements, which is then rapidly resolved during a short time window prior to the announcement and brings a significant price appreciation.

Other papers examine the timing of the stock market to incorporate macroeconomic news. Lucca and Moench (2015) find that about 80% of annual realized excess stock returns since 1994 are accounted for by the return drift in the 24 hours before scheduled FOMC announcements. Kurov et al. (2019) also find that nine of the 20 scheduled economic news is incorporated by the price of the stock index futures and Treasury futures ahead of the official release time. Bernile, Hu and Tang (2016) find that the E-mini Standard & Poor's 500 futures' abnormal order imbalances can predict the market reaction to the FOMC announcements. Other papers (Vissing-Jorgensen (2020), Hu et al. (2019)) also highlight the possibility of information leakage ahead of scheduled macroeconomic news.

My study is closer to the second strand of literature which investigates information leakages ahead of scheduled macroeconomic news. My paper differs from extant literature by providing evidence on the trading behaviour in the financial market around macroeconomic news. This evidence sheds light on one important question: does the economic news leakage, if ever exists, apply to all investors or only a certain group of investors? My findings are more in line with the second view.

This paper also contributes to literature that studies the trading behaviour around public news. Tetlock (2010) finds earning announcements resolve information asymmetries between informed investors and liquidity traders. Nevertheless, the paper only discusses the trading volume increase after public news announcements. The volume dynamics around macroeconomic announcements documented by my paper, is similar to the one around scheduled corporate earning announcements in Chae (2005). My paper highlights information asymmetries among investors in anticipation of macroeconomic announcements.

My findings are also relevant to a few papers that use equilibrium models to understand the excess stock returns on days with macroeconomic announcements. To my knowledge, current theories (Ai and Bansal (2018), Wachter and Zhu (2018)) attribute the macroeconomic announcement premium to the resolution of preference uncertainties. Since these models only aim at explaining the risk premium, the authors use representative-agent models to simplify their studies and lack implications on trading volumes. In contrast, my findings show that the information might leak to a certain group of investors so that their uncertainties are resolved in advance. As a result, liquidity traders prefer to postpone exogenous trade demands they receive prior to announcements until the information asymmetry is resolved (Admati and Pfleiderer (1988), Foster and Viswanathan (1993), Kim and Verrecchia (1994)). Because of this strategic trading behaviour of liquidity traders, a larger share of market risk will be borne by the investors that still trade in the market before macroeconomic announcements. A model that captures the redistributions of market risk among informed and uninformed investors (Duffie (2010), Dow and Han (2018)), may potentially explain both the price and volume dynamics around economic news. Further studies can also contribute to the current literature by disentangle the amount of premium that is attributed to the resolution of uncertainties from the amount that is attributed to the redistribution of market risk.

3 Sample construction

3.1 Individual stocks

My analysis focus on the volume dynamics of a market ETF (SPDR S&P 500 ETF) and individual stocks around scheduled macroeconomic announcements. The intraday trade data for all securities listed on main exchanges in US are available from the NYSE database since 1993. However, given the long time span this study tries to focus on and given the limitation of computing power, it is not feasible to obtain the tick-by-tick trade records for all listed securities.

Therefore, I limit my study to the SPDR S&P 500 ETF and the individual stocks that have been included in the S&P 500 index for at least over a year. They are in general more actively traded than smaller stocks so that my results are not biased by small illiquid stocks. I first identify the constituent lists for the S&P 500 index from COMPUSTAT and their trading symbols. Then I obtain from WRDS the second-by-second matched trades and NBBO midpoints for all S&P 500 stocks during regular trading hours.

Besides the high-frequency trades data, I also construct several firm characteristics as explanatory variables or control variables. Using data from CRSP, I define *Size* as the product of absolute price and number of outstanding shares of a stock from the previous day, expressed in 100 billions of dollars. *Momentum* is defined using the cumulative returns of a stock over the previous year. Two liquidity characteristics are constructed—*Amihud* is the average ratio between daily absolute return and dollar volume; *Monthly turnover* is the average logarithm turnover in the previous month. *Beta* is estimated using the Fama-French 3 factor model with daily-frequency return data over the previous year. Using the same factor model with data from the previous month, I construct the *idiosyncratic risk* characteristic as the volatility of the residual term from CAPM regressions. Using the balance sheet data from the Standard and Poor's Compustat database, I also construct the book value of a company following Gorodnichenko and Weber (2016). Table 15 lists the formal definition of each control variable. For each stock, I also obtain the number of institutional owners who are required to file 13F forms from Thomson Reuters. Finally, I remove firms with negative book values and stocks that have not been traded for 12 consecutive working days.

From 1993–2014, the matched trades and quotes data on WRDS are retrieved from NYSE's Monthly Trade and Quote (MTAQ) database, timestamped to the second and use trading symbols as stock identifiers. After 2014, WRDS only provides matched data based on the NYSE's Daily Trade and Quote (DTAQ) database, timestamped to the millisecond and use the combination of symbol roots and suffix as stock identifiers. To match the trades dataset with the CRSP dataset, I first use the MTAQ-CRSP linktable from WRDS to map trading *symbols* in the MTAQ database to *permno* in the CRSP database at the monthly basis for observations up to 2003. For observations after 2004, I use the DTAQ-CRSP linktable to map trading *symbol roots* to *permno* in the CRSP database. On a given day, there might some cases that *permno* in the CRSP database is mapped to multiple trading symbols or symbol roots. These are very rare cases and I remove such stocks from my dataset. The FOMC committee started to regularly release their interest rate decisions since September 1994. I restrict the sample to observations after this date. After matching the trade data with firm-level characteristics, the final dataset includes over 2 millions of observations for 765 unique common stocks and 5979 trading days spanning from September 1994 to May 2018.

3.2 Macroeconomic announcements

My study focus on the volume dynamics around the official release of three out of the ten most closely watched economic indicators listed on Bloomberg—the Federal Open Market Committee announcement (FOMC), the purchases of manufacturing index (hereafter, PMI) and the monthly unemployment rate (hereafter, unemployment). I manually collect the official announcement times of these macroeconomic news following Lucca and Moench (2015).

The FOMC meetings usually span over two days and it is on the second day that policy decisions are released. From September 1994 to May 1999, the FOMC regularly release a statement at or a few minutes after 2:15 p.m.[5] following each scheduled meeting at which a policy action was initiated [6]. On March 24, 2011, the Federal Reserve announced that Chairman Bernanke would hold quarterly press conferences coinciding with the Federal Open Market Committee (FOMC) meetings where participants submit their economic projections. Since then, the FOMC have introduced two extra forms to communicate with the market–the press conferences and the FOMC members' economics projections (SEP). The Chair of FOMC has been giving a press conference at every other FOMC meeting after the April 2011 meeting. In 2011 and 2012, FOMC statements that were scheduled with a press conference were released at 12:30 p.m., and the press conference started at 2:15 p.m. FOMC statements without a press

[5]The only exception to the time of the announcement is the statement of March 26, 1996, which was released in the morning because the chairman was scheduled to testify in Congress later that day. This meeting is excluded from my event study.

[6]Otherwise, the FOMC announced that no statement would be released, indicating to investors that no policy action had been taken.

conference were released at 2:15 p.m. as in the pre-2011 sample. Starting in 2013, FOMC statements were always released at 2:00 p.m., while press conferences started at 2:30 p.m. On June 13, 2018, Chairman Powell announced he would begin holding press conferences after every FOMC meeting beginning January 2019. My sample period ends in May 2018, before this change is initiated. From Sep 1994–May 2018, the total number of scheduled FOMC announcements is 189.

The Institute for Supply Management (ISM) Manufacturing Business Survey Committee typically release the manufacturing purchase index (PMI) on the first Monday of each month. Meanwhile, statistics regarding the employment situation of the previous month is reported by the U.S. bureau of labor statistics on the first Friday of each month. Both statistics are used by investors as leading indicators of economic health, given their insight into sales, employment, inventory, and pricing. They are among the most highly watched economic indicators since they are often the first major surveys released in each month. PMI is always released at 10:00 am Eastern Time and the labor statistic is always released at 8:30 am Eastern Time. PMI starts to be compiled since January 1996 and I collect its release dates from Bloomberg. From January 1996 to May 2018, the total number of PMI releases is 259. Historical dates with labor statistics announcements are available on the website of the U.S. bureau of employment statistics. From September 1994–May 2018, the total number of releases of employment statistics is 290. Table 1 provides a summary of the scheduled release times of these three types of macroeconomic news.

4 A preliminary analysis around FOMC announcements

In this section, I investigate the volume dynamics of S&P500 ETF (SPDR) around FOMC announcements as a representative asset for the equity market. In the first subsection, I describe how a stationary volume measure is constructed. Afterwards, I discuss the contemporaneous relation between volume and volatility around FOMC announcements.

4.1 The volume dynamics of SPDR

I look for a measure to capture the daily abnormal trading activities in relative to its historical trend. Since the number of shares outstanding and the number of shares traded have both grown steadily over time, I use turnover rather than share volume or dollar volume to reduce the low-frequency variation in the volume series. Nevertheless, the top chart in Figure 5 shows that even the level of turnover is not stationary. The level of turnover seems to be related to business cycles and exhibit low-frequency persistence. Moreover, the variance of turnover seems to increase with its level.

In order to mitigate the low-frequent variation in the level of turnover, I follow Campbell, Grossman and Wang (1993) and transform it into a stationary time series that: 1. removes low-frequency variations from the variance by using log turnover rather than levels; 2. removes low-frequency variations from the level by subtracting the one-month moving average of log turnovers. In the rest of this paper, I refer to the monthly detrended log turnover to *abnormal turnover*. The bottom chart in Figure 5 shows that the abnormal turnover of SPDR no long exhibits trends in mean or variance.

To show the volume dynamics from a high-frequency perspective, I first construct the detrended log turnover for SPDR by each five-minute trading window. Formally, the abnormal turnover of SPDR at time h on day d is defined as the logarithm of turnover at time h, detrended by its average value in the previous month:

$$\tau_{h,d} = log(\frac{V_{h,d}}{shrout_d}) - \frac{1}{22}\sum_{k=1}^{22} log(\frac{V_{h,d-k}}{shrout_{d-k}}), \tag{1}$$

where $V_{h,d}$ is the trading volume at time h on day d; and $shrout_d$ is total number of outstanding shares on day d. By construction, an increase of 0.1 unit in $\tau_{h,d}$ indicates the turnover at time h increases approximately by 10% on day d comparing to its past monthly average level.

Figure 6 presents the average abnormal turnover by each five-minute trading window of SPDR over day triplets. The blue solid line in the figure shows the average abnormal turnover over a 48-hours window centering around a FOMC announcement. I also randomly draw 3,000 non-announcement days and the red dashed line shows the average abnormal turnover

over a 48-hours window around these days. The abnormal turnover is on average close to zero on non-announcement (*NonFOMC*) days. In contrast, the abnormal turnover of SPDR in anticipation of FOMC announcements is negative and significantly below the red dashed line. After FOMC statements being announced, the abnormal turnover of SPDR increases rapidly and continues to significantly exceed its past monthly average in the following day.

Having illustrated the volume dynamics in SPDR from a high-frequency perspective, I construct the daily abnormal turnover for statistical tests. In order to compare the abnormal turnover before and after FOMC announcements and because FOMC announcements are typically released within 15 minutes after 2 p.m., I follow Lucca and Moench (2015) and redefine a trading day d as the 24-hours window from 2 p.m. on calendar day $d-1$ to 2 p.m. on calendar day d. If an announcement is released on calendar day d, then the abnormal turnover on day d reflects trading activities in the 24-hours window before the announcement by construction. Likewise, the abnormal turnover on day $d+1$ reflects trading activities in the 24-hours window after the announcement. From now onward, the daily abnormal turnover in this paper represents for the abnormal turnover constructed within the 2pm-2pm window based on the following equation:

$$\tau_{i,d} = log(\frac{V_{i,d}}{shrout_{i,d}}) - \frac{1}{22}\sum_{k=1}^{22} log(\frac{V_{i,d-k}}{shrout_{i,d-k}}), \tag{2}$$

where $\frac{V_{i,d}}{shrout_{i,d}}$ is total turnover of stock i from 2 p.m. on calendar day $d-1$ to 2 p.m. on calendar day d.

In order to test the statistical significance of the volume dynamics around FOMC announcements, I regress the daily abnormal turnover of SPDR on event dummies and report the results in Table 4. Results in the first column implies that SPDR is traded about 12.265% less than its past monthly trend in the 24 hours before scheduled FOMC announcements.

Table 2 provides the summary statistics for SPDR for pre-(post-) FOMC 24-hour windows and for all other time. The average daily dollar volume of SPDR is about 10.5 billion dollars on $NonFOMC$ days in the sample period from Sep 1994–May 2018. A 12.265% decline in turnover of SPDR therefore implies that transactions in anticipation of FOMC announcements drop by about 1.29 billion dollars. This result is also robust after controlling for other variables that may cause temporary volume changes. After FOMC announcements, turnovers increase by about 28.132% comparing with the average turnover in the previous month.

4.2 Volume and volatility

Volumes and volatilities usually move in tandem. An extensive empirical literature has documented the existence of a strong positive contemporaneous relation between trading volume and price volatility (see Karpoff (1987) for a survey). Therefore, it is natural to ask whether the volume dynamics around FOMC announcements is related to an exogenous change in macroeconomic risk. To answer this, in Table 5 I regress the daily volatility of SPDR on FOMC-related event dummies. To match with the construction window of abnormal turnovers, I define daily volatility on day d as the absolute value of the percentage return from $2pm$ on calendar day $d-1$ to $2pm$ on calendar day d. The left panel in Table 5 uses the absolute return as dependent variables. In the first column, the coefficient on the $PreFOMC$ dummy is 0.131 with a Newey and West (1987) standard error of 0.05. This coefficient is both economically and statistically significant. The average absolute return is about 0.626% in the sample period. Therefore, the estimated coefficient 0.131 implies that the price volatility measured by absolute returns declines by 20.5% (= 0.131/0.636) in the 24 hours before scheduled FOMC announcements. The coefficient on the $PostFOMC$ dummy is 0.122 and statistically different from 0 after controlling for the day-of-week effect. This result indicates that the price volatility increases by 19.2% (= 0.122/0.636) due to the arrival of FOMC announcements.

In the second column of Table 5, I add abnormal turnover as an additional explanatory variable and also interact it with dummy variables. When abnormal turnover enters the regression, R^2 of the regression increases from 0.0022 to 0.0349. The coefficient on the $PreFOMC$ dummy is still both economically and statistically significant. However, the coefficient on the $PostFOMC$ dummy becomes insignificant. This result indicates that the increase in price volatility after FOMC announcements is likely induced by trading activities upon the arrival of announcements. Nevertheless, it is unlikely that pre-FOMC announcement decline in price volatility is also attributed to contemporaneous volume changes. Instead, this decline in volatility is consistent with previous studies that find macroeconomic uncertainties are resolved before scheduled FOMC announcements (Ai and Bansal (2018), Wachter and Zhu (2018), Hu et al. (2019)).

Daily price volatility is highly persistent (Campbell, Grossman and Wang (1993), Jones, Lamont and Lumsdaine (1998)) and this may potentially make the OLS estimates unreliable. To mitigate this issue, I detrend the log absolute return by its past monthly average value, similar to the construction of abnormal turnovers. In the right panel of Table 5, I use the percentage of detrended log absolute return as the dependent variable. Column 3 shows that the price volatility decline by 28.823% on $PreFOMC$ days in relative to its past monthly average. This estimate drops to 22.39% after adding abnormal turnover and interaction terms into the regression. The 22.39% decline in relative to the past monthly average is similar to the estimated value in relative to the unconditional average in the left panel (0.115/0.636). Column 4 shows that the coefficient on the $PostFOMC$ dummy turns into negative when abnormal turnovers enters the regression. This result is consistent with Column 2 and implies that the increase in price volatility after FOMC announcements is likely induced by trading activities.

Having showed that price volatility has changed around FOMC announcements, I ask if it helps explain the volume dynamics around announcements. To answer this, I regress the daily abnormal turnover of SPDR on price volatility. The first column in Table 6 only includes the FOMC-related dummies and the result repeats the same column in Table 4. It shows that the turnover of SPDR declines by 12.265% in the 24 hours before scheduled FOMC announcements and increases by 28.132% afterwards. When absolute return enters the regression, the second column shows that R^2 increases from 2.13% to 5.31%. The coefficient on absolute return is 9.924 and statistically significant. This implies that one standard deviation (0.66% on $NonFOMC$ days) increase in absolute return is on average associated with 6.59% ($= 0.66\% \times 9.924$) increase in turnover. However, coefficients on the interaction terms show that the correlation between volume and volatility do not provide additional power in explaining abnormal turnover around FOMC announcements. Coefficients on both dummy variables are essentially unchanged after including price volatility to the regression. In the last two columns, I use the detrended log absolute return as an alternative measure of price volatility. Results also imply that the turnover dynamics around FOMC announcements can not be explained by the change in price volatility. Therefore, I conclude that the volume dynamics around FOMC announcements is unlikely to attribute to exogenous volatility shocks.

The pre-announcement decline in volatility is not explained by the contemporaneous change in volume, and therefore it is likely that this volatility change is exogenous. Inspired by the timing of this volatility change, I assume that information leaks to a certain group of investors ahead of FOMC announcements. In the following section, I develop a model based on private information to explain the volume dynamics around FOMC announcements.

5 A stylized model with private information

In this section, I develop a two-period rational expectation equilibrium model to guide further investigations of volume dynamics around macroeconomic announcements. The model relies on three key assumptions. Firstly, the price is set by market makers based on the total order flow they observe. Secondly, some liquidity traders are discretionary. Thirdly, a group of sophisticated investors have superior information-processing capabilities. Similar models include Admati and Pfleiderer (1988) and Kim and Verrecchia (1994).

5.1 Model setup

The model consists of three dates ($t = 1,2,3$) and one risky asset. The risky asset has an uncertain payoff of $F = \beta\theta + e_1 + e_2 + e_3$ in the final period. $e_t \sim N(0, \sigma_e^2)$ is a random shock becomes publicly available in period $t+1$. $\theta \sim N(0, \sigma_\theta^2)$ captures the payoff from the aggregate economy and is revealed publicly in period $t = 2$. β measures the correlation between the payoff of the individual asset and the payoff of the aggregate economy.

There are four types of market participants in the market: one informed investor, two units mass of discretionary liquidity traders, one noise trader and one market maker. In the initial period, informed investors receive a private signal that perfectly reveals the value of θ. Moreover, informed traders observe something about the piece of public information that will be revealed one period later to all traders. In each period t, the random component e_{t+1} in the final payoff is observed by informed investors through private channels. The structure of private information is similar to the one in Admati and Pfleiderer (1988). One interpretation of this structure is that privately informed traders are able to process public information faster or more efficiently than others are. Since the private information becomes useless one period after it is observed, informed traders only need to determine their trade in the period in which they are informed. Under this structure of private information, the order flow in each period is independent to each other.

There are two classes of liquidity traders. In each period, the noise trader must trade $z_t \sim N(0, \sigma_z^2)$ shares in that period. The other group of liquidity traders consists of traders who have liquidity demands that need not be satisfied immediately. They are called *discretionary liquidity traders* and their demand for shares is determined in period t and needs to be satisfied before $t+1$. One unit mass of the discretionary liquidity traders receive their liquidity demands in period $t = 1$ and the rest receive their liquidity demands in period $t = 2$. The liquidity demand of each discretionary liquidity trader is normally distributed with mean 0 and variance σ_d^2. Distributions of liquidity demands are independent for different traders and in different periods. Distributions for all random variables in this model are mutually independent.

The time line below summarizes the key events in the model:

$t = 1$	$t = 2$	$t = 3$
Informed investors observes the signal θ and e_1. Discretionary liquidity traders receive independent liquidity shocks.	Public news reveals θ. Informed investors observes the signal e_2. e_1 is revealed to the public. Discretionary liquidity traders receive independent liquidity shocks.	Informed investors observes the signal e_3. e_2 is revealed to the public. The liquidation value F is revealed at end of the final trading period.

In each period, investors submit their orders to market makers, whose pricing response is assumed to be a linear function of the history of order flows and public information up to period $t-1$. All market participants are risk neutral and they trade to maximize their utility in the final period.

As previously mentioned, e_t is private information for only one period. Under this assumption, market makers' expectation on the final payoff is only related to the contemporaneous order flow, not to historical order flows. In period t, market makers set the price following a linear function of the contemporaneous order flow and public information and:

$$P_3 = E[F|(\theta, e_1, e_2, \omega_3)] = \lambda_3\omega_3 + e_1 + e_2 + \beta\theta, \tag{3}$$

$$P_2 = E[F|(\theta, e_1, \omega_2)] = \lambda_2\omega_2 + e_1 + \beta\theta, \tag{4}$$

$$P_1 = E[F|\omega_1] = \lambda_1\omega_1, \tag{5}$$

where ω_t is the total order flow in period t and λ_t captures the impact of order flow on price.

In period 3, the informed investor submits her order to maximize the expected utility:

$$U_3 = \max_{x_3} E[(e_1 + e_2 + e_3 + \beta\theta - P_3)x_3|(e_1, e_2, e_3, \theta)], \tag{6}$$

where x_3 is demand from the informed investor and P_3 is equilibrium price in period $t = 3$. Substitute equation 3 into equation 6 and the optimal informed demand is:

$$x_3 = \frac{e_3}{2\lambda_3}. \tag{7}$$

That is, if the private signal e_3 is positive, the informed investor will buy the asset; otherwise, the informed investors will sell the asset. The parameter $\frac{1}{2\lambda_3}$, capture the aggressiveness of informed investors. Informed investors are more aggressive to trade when the price impact λ_3 is low. Similarly, the optimal informed demand in other periods are:

$$x_2 = \frac{e_2}{2\lambda_2}, \tag{8}$$

$$x_1 = \frac{e_1 + \beta\theta}{2\lambda_1}. \tag{9}$$

In period t, discretionary liquidity traders who receive liquidity demands decide the timing of trade to minimize their trading costs. They could trade either in period t or in period $t+1$. However, if they postpone tradings to the next period, discretionary liquidity traders have to bear a positive inventory cost c. Each liquidity trader expects the price to be a linear function of her price impact. As a result, if the j^{th} liquidity trader who receives a liquidity demand D_j in period t decides to trade immediately, her expected cost will be:

$$E[P_t|D_j]D_j = \lambda_1 {D_j}^2; \tag{10}$$

otherwise, her expected cost is,

$$E[P_{t+1}|D_j]D_j = \lambda_2 {D_j}^2 + c|D_j|. \tag{11}$$

The total order flow in period t is the sum of four independently normal distributions:

$$\omega_t = x_t + \sum_{j\in\mathbb{S}_t^{t-1}} D_j + \sum_{k\in\mathbb{S}_t^t} D_k + z_t, \tag{12}$$

where $\mathbb{S}_t^{t-1}$ is the set of discretionary liquidity traders who receive liquidity demands in period $t-1$ but trade in period t; and $\mathbb{S}_t^t$ is the set of discretionary liquidity traders who receive liquidity demands in period t and trade immediately. The first part in equation 12 is the demand from informed investors. The second and third parts represent for the order flow from discretionary liquidity traders who trade in period t. The last component is the order flow from noise traders.

I follow Kyle (1985) and derive the equilibrium of the model by backward induction. First of all, consider the group of discretionary liquidity traders who receive liquidity demands in period $t = 2$. This group of investors can choose to trade either in period $t = 2$ or $t = 3$. It is straightforward that immediate executions are always the optimal strategy for these traders. Then according to equation 12, order flows in each period can be rewritten as:

$$\omega_3 = x_3 + z_3, \tag{13}$$

$$\omega_2 = x_2 + \sum_{j \in \mathbb{S}_2^1} D_j + \sum_{k \in \mathbb{S}_2^2} D_k + z_2, \tag{14}$$

$$\omega_1 = x_1 + \sum_{j \in \mathbb{S}_1^1} D_j + z_1, \tag{15}$$

where $\mathbb{S}_{t_2}^{t_1}$ is the set of discretionary liquidity traders with demands determined in period t_1 but trade in period t_2.

In each period, the order flow ω_t is a normally distributed signal for private signals. Based on the Bayes' law, market makers' conditional expectation on the final payoff in period $t = 3$ is:

$$E_3[F] := E[F|(\theta, e_1, e_2, \omega_1, \omega_2, \omega_3)] \tag{16}$$

$$= E[e_3|\omega_3] + e_1 + e_2 + \beta\theta \tag{17}$$

$$= \gamma_3\omega_3 + e_1 + e_2 + \beta\theta, \tag{18}$$

where

$$\gamma_3 = \frac{2\lambda_3 \frac{\sigma_e^2}{4\lambda_3^2}}{\frac{\sigma_e^2}{4\lambda_3^2} + \sigma_z^2}. \tag{19}$$

Among discretionary liquidity traders who receive liquidity demands in period $t = 1$, let α_1 (and $\alpha_1 \in [0, 1]$) be the fraction who trade in period $t = 1$; and $1 - \alpha_1$ be the fraction who trade in period $t = 2$. Then the conditional expectation on the final payoff in other periods is:

$$E_2[F] := E[F|(\theta, e_1, \omega_1, \omega_2)] = E[e_2|\omega_2] + e_1 + \beta\theta = \gamma_2\omega_2 + e_1 + \beta\theta, \tag{20}$$

$$E_1[F] := E[F|(\theta, \omega_1)] = E[e_1|\omega_1] = \gamma_1\omega_1, \tag{21}$$

where

$$\gamma_2 := \frac{2\lambda_2 \frac{\sigma_e^2}{4\lambda_2^2}}{\frac{\sigma_e^2}{4\lambda_2^2} + (1-\alpha_1)^2\sigma_d^2 + \sigma_d^2 + \sigma_z^2}, \tag{22}$$

$$\gamma_1 := \frac{2\lambda_1 \frac{\sigma_e^2+\beta^2\sigma_\theta^2}{4\lambda_1^2}}{\frac{\sigma_e^2+\beta^2\sigma_\theta^2}{4\lambda_1^2} + \alpha_1^2\sigma_d^2 + \sigma_z^2}. \tag{23}$$

In equilibrium, the zero-profit condition implies that market makers always set the price equivalent to their expectation on the final payoff (i.e. $P_t = E_t[F]$). Therefore, the equilibrium price impact λ_t is the solution to the fixed point problem $\lambda_t = \gamma_t$. By solving these equations, I obtain the equilibrium price impact for each period t:

$$\lambda_3 = \frac{\sigma_e}{2\sigma_z}, \tag{24}$$

$$\lambda_2 = \frac{1}{2}\sqrt{\frac{\sigma_e^2}{(1-\alpha_1)^2\sigma_d^2 + \sigma_d^2 + \sigma_z^2}}, \tag{25}$$

$$\lambda_1 = \frac{1}{2}\sqrt{\frac{\sigma_e^2 + \beta^2\sigma_\theta^2}{\alpha_1^2\sigma_d^2 + \sigma_z^2}}. \tag{26}$$

Having found the equilibrium price impact in each trading period, I look for the optimal trading strategy of discretionary liquidity traders who receive liquidity demands in period $t = 1$. The equilibrium value of α_1 is determined by the price impact functions (λ_1, λ_2), the inventory cost (c) and the volatility of discretionary liquidity demand (σ_d). Although the equilibrium exists, it is hard to find a closed-form solution for α_1. In the appendix, I show that when σ_θ is sufficiently large, the problem will be greatly simplified and the model has a unique equilibrium.

Because the price impact in period $t = 1$ is higher than the price impact in period $t = 2$, [7], traders with large liquidity demand in period $t = 1$ will prefer to trade with a delay. Recall that c captures the inventory cost of delaying the transaction. It can be shown that for liquidity traders with large demands (more specifically, when $|D_j| \geq \frac{c}{\lambda_1 - \lambda_2}$) , immediate executions in the period with high price impact are more costly than carrying them to the next period with low price impact.

5.2 Testable implications

Formally, the equilibrium value of α_1 is determined by the following condition,

$$Prob\left(|D_j| \leq \frac{c}{\lambda_1 - \lambda_2}\right) = \alpha_1, \tag{27}$$

which can be rewritten as:

$$\alpha_1 = 2\Phi\left(\frac{c}{\lambda_1 - \lambda_2}\right), \tag{28}$$

where $\Phi(\cdot)$ is the cumulative distribution function of a normal distribution with mean 0 and variance σ_d^2. The difference in price impacts across two periods, $\lambda_1 - \lambda_2$, determines the distribution of liquidity traders. A higher value of $\lambda_1 - \lambda_2$ implies that the announcement of macroeconomic signals resolves more information asymmetries. As a result, trading in the first period is relatively more expensive and the number of first-period discretionary liquidity traders α_1 decreases.

Theorem 1 *When σ_θ^2 is sufficiently large, equation 28 always has a unique solution. At equilibrium, the number of liquidity traders who trade at the first trading period is smaller for assets that are more exposed to the macroeconomic risk.*

Proof. The formal proof is in the appendix. ■

[7] $\lambda_1 - \lambda_2$ is always positive. The difference between price impacts, $\lambda_1 - \lambda_2$, is decreasing in α_1. The minimal value is achieved at the point $\alpha_1 = 1$. Therefore, $\lambda_1 - \lambda_2 \geq min(\lambda_1 - \lambda_2) = \sqrt{\frac{\sigma_e^2+\beta^2\sigma_\theta^2}{\sigma_d^2+\sigma_z^2}} - \sqrt{\frac{\sigma_e^2}{\sigma_d^2+\sigma_z^2}} > 0$ as long as $\beta_> 0$.

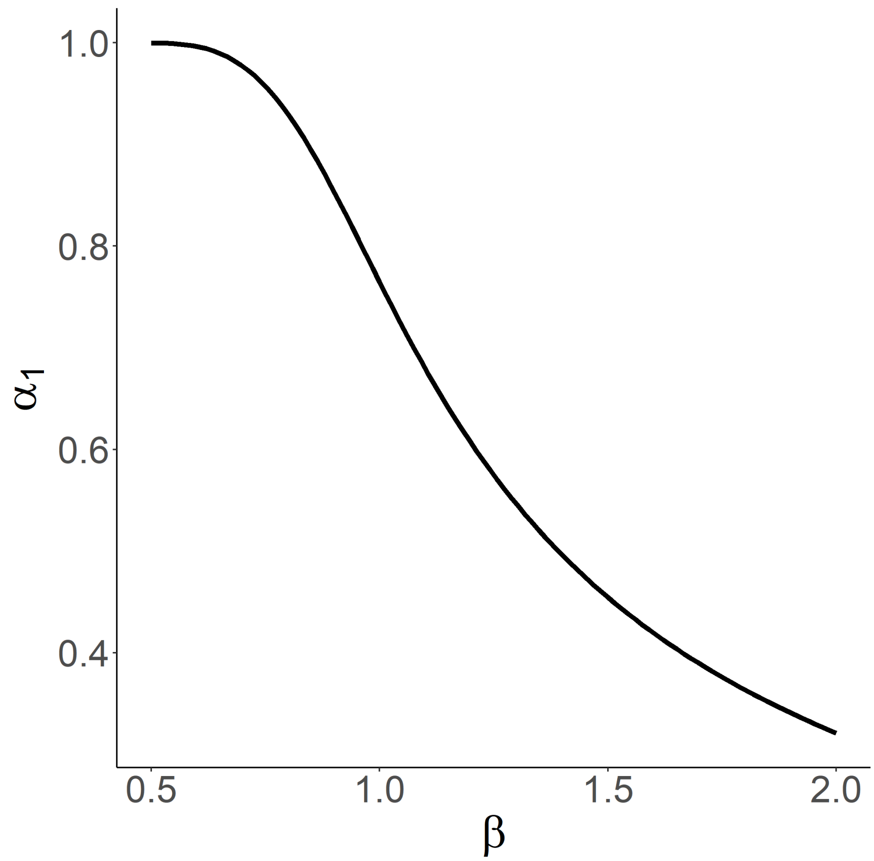

Figure 1: This graph plots α_1 against β. Values of exogenous parameters are $\sigma_e^2 = 1$, $\sigma_d^2 = 1$, $\sigma_z^2 = 1$, $\sigma_\theta^2 = 8$, $c = 1$.

Nevertheless, the behavior of discretionary liquidity traders are not observable in reality. Following Theorem 1, I investigate the relation between the trading volume and an asset's exposure to the macroeconomic risk. Let V_t be the total trading volume at time t. Admati and Pfleiderer (1988) demonstrate that the expected trading volume equals to the half of sum of the absolute demand from each trader. Therefore, the expected trading volume in the first period can be written as,

$$E[V_1] = \frac{1}{2}\left\{E[|x_1|] + \sum_{j \in \mathbb{S}_1^1} E[|D_j^1|] + E[|z_1|]\right\} = \sqrt{\frac{1}{2\pi}}\left(\sqrt{\alpha_1^2\sigma_d^2 + \sigma_z^2} + \alpha_1\sigma_d + \sigma_z\right). \quad (29)$$

Likewise, the expected trading volume in the second period is,

$$E[V_2] = \frac{1}{2}\left\{E[|x_2|] + \sum_{j\in\mathbb{S}_2^1} E[|D_j^1|] + E[|D_2^k|] + E[|z_2|]\right\} \tag{30}$$

$$= \sqrt{\frac{1}{2\pi}}\left(\sqrt{(1-\alpha_1)^2\sigma_d^2 + \sigma_d^2 + \sigma_z^2} + (2-\alpha_1)\sigma_d + \sigma_z\right). \tag{31}$$

Now consider a benchmark case in which the public news announcement about the aggregate economy does not matter: $\beta = 0$ or the common factor θ does not exist. Then it is always optimal for discretionary liquidity traders to trade immediately when they receive liquidity demands. In equilibrium, the trading volume and the price impact are both constant across different time periods,

$$V^b = \sqrt{\frac{1}{2\pi}}\left(\sqrt{\sigma_d^2 + \sigma_z^2} + \sigma_d + \sigma_z\right), \tag{32}$$

and,

$$\lambda^b = \frac{1}{2}\sqrt{\frac{\sigma_e^2}{\sigma_d^2 + \sigma_z^2}}. \tag{33}$$

It is easy to see that $E[V_1] \leq V^b \leq E[V_2]$.

Theorem 2 *When σ_θ^2 is sufficiently large, the trading volume in period $t = 1$ is below the volume under the benchmark case without public signals; while the trading volume in period $t = 2$ is above the volume under the benchmark case. Moreover, the magnitude of volume change around macroeconomic announcements increases in an asset's exposure to the macroeconomic risk.*

Figure 2 illustrates the relation between volume changes and an asset's exposure to the macroeconomic risk. The volume change around the public announcements of θ is greater for high-β assets than for low-β assets. The reason is that the fraction of first-period discretionary liquidity trader, α_1, is decreasing in β. Consequently, the magnitude of volume change around macroeconomic announcements increases in an asset's exposure to the macroeconomic risk.

It is also worth to mention that without macroeconomic announcements, the trading volume is not directly related to an asset's exposure to the systematic risk. The trading volume,

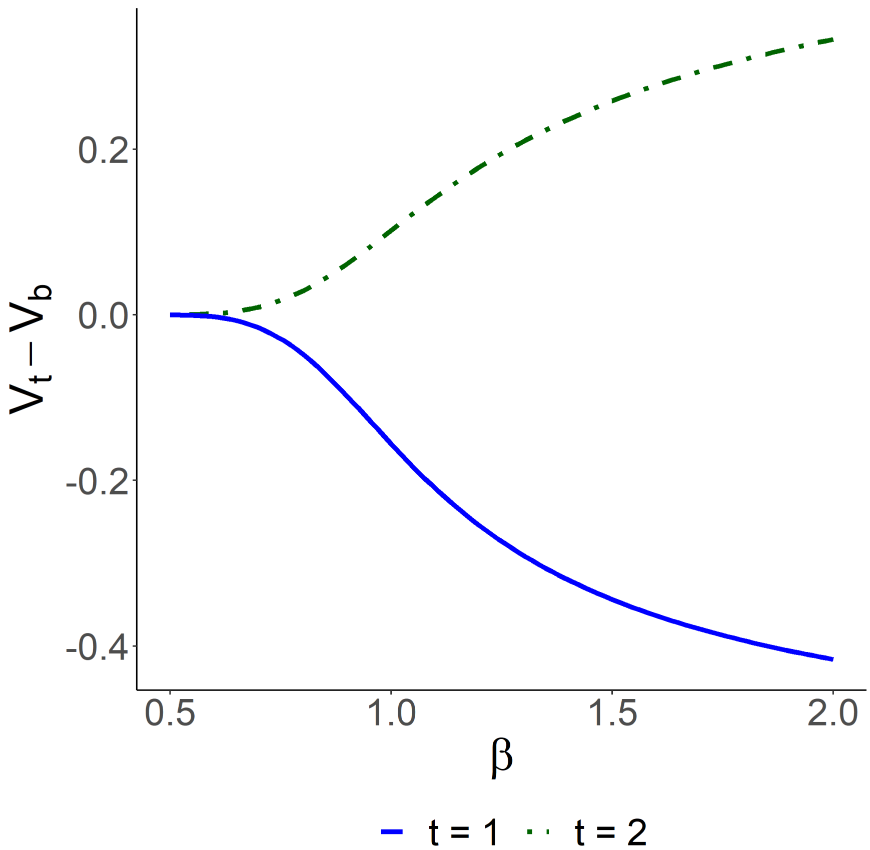

Figure 2: This graph plots volumes (V_t) around the announcement of θ in relative to the benchmark volume (V_b) against β. Values of exogenous parameters are $\sigma_e^2 = 1$, $\sigma_d^2 = 1$, $\sigma_z^2 = 1$, $\sigma_\theta^2 = 8$, $c = 1$.

however, monotonically increases in the variance of discretionary liquidity trading, σ_d^2. Because discretionary liquidity traders (Admati and Pfleiderer (1988)) are usually large institutions who have relatively high risk appetites, risky assets also tend to be exposed to move volatile discretionary liquidity tradings. This might explain why assets with a higher systematic risk are usually found to exhibit higher trading volumes comparing with assets with a lower systematic risk.

The price impact in period $t = 1$ is higher than the price impact in period $t = 2$ for two reasons. Firstly, informed investors receive not only z_1 but also θ as private information in this period. The probability of informed trading is therefore higher in the first period. Secondly, a $1-\alpha_1$ fraction of discretionary liquidity traders postpone their liquidity tradings to the next period. This further amplify the probability of informed tradings and results in a higher price impact parameter λ_1. In the cross section, the change in price impact around macroeconomic announcements decreases in an asset's exposure to the macroeconomic risk. That is, $\frac{\partial(\lambda_2-\lambda_1)}{\partial\beta} < 0$.

Theorem 3 *When σ_θ^2 is sufficiently large, the price impact in period $t = 1$ is higher than the price impact in period $t = 2$. Moreover, the change in price impact around public news announcements, $\lambda_2 - \lambda_1$, decreases in an asset's exposure to the macroeconomic risk.*

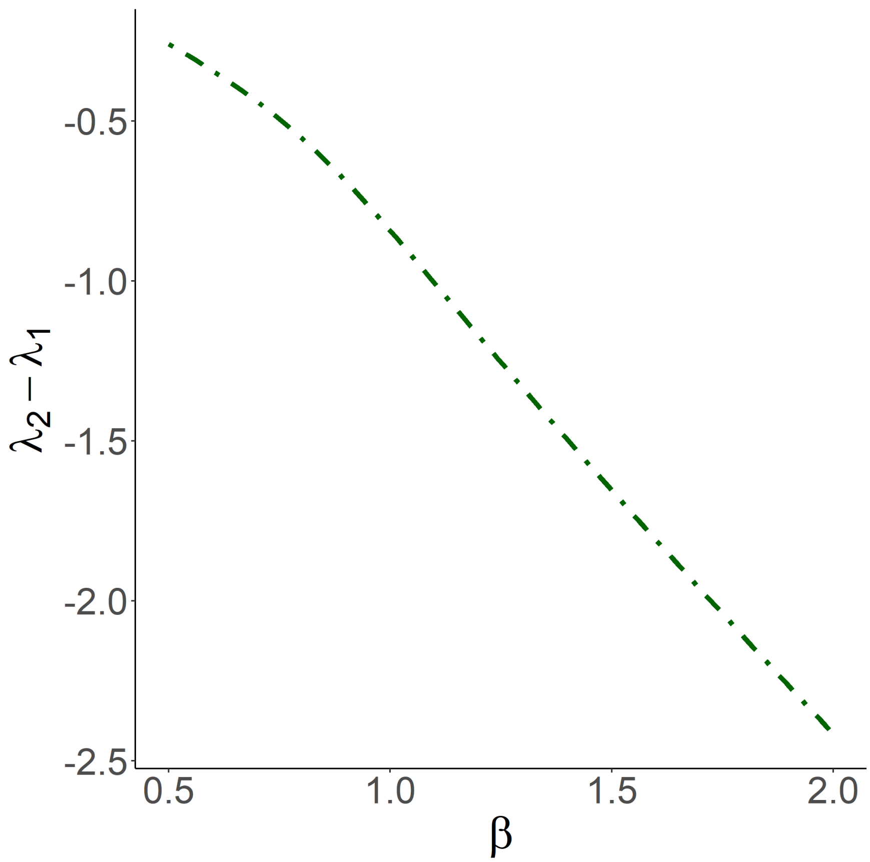

Figure 3: This graph plots the change in price impacts $(\lambda_2 - \lambda_1)$ around the announcement of θ against β. Values of exogenous parameters are $\sigma_e^2 = 1$, $\sigma_d^2 = 1$, $\sigma_z^2 = 1$, $\sigma_\theta^2 = 8$, $c = 1$.

Having established the relation between volume, price impact and an asset's systematic risk around macroeconomic announcements, in the following section, I present the empirical results following the theoretical guidance.

6 Evidence from the cross section

In previous sections, I have showed that the turnover in SPDR decreases by over 12% in anticipation of FOMC announcements and increases by about 28% afterwards, relative to their past monthly averages. The volume dynamics in SPDR around FOMC announcements is consistent with a model with private information and discretionary liquidity tradings. When informed investors observe a signal about the aggregate economy, information asymmetry increases and some discretionary liquidity traders may choose to postpone their liquidity demands. The model therefore predicts a volume decline in anticipation of macroeconomic announcements and increase afterwards. Apart from the market-wise evidence, the model also has implications in the cross section. The payoff of individual assets usually comoves with the aggregate economy. For this reason, liquidity traders who trade stocks comoves more with the economy should have stronger incentives to postpone their tradings because they bear more information asymmetries in anticipation of macroeconomic announcements. According to the prediction of Theorem 2, high-beta assets should experience greater volume changes around macroeconomic announcements than low-beta assets.

6.1 Volume and systematic risk

In this section, I show empirical evidence that macroeconomic announcements cause greater volume changes among stocks with higher systematic risks. I first calculate the daily abnormal turnover for each stock. Then on each day, I divide individual stocks into quantile groups according to their market betas estimated from one-year rolling CAPM regressions. Table 3 provides summary statistics for individual stocks for variables that will be used in the empirical analysis.

Figure 4 plots the value-weighted abnormal turnover of each portfolio against their market betas. The middle line shows that the average abnormal turnover is essentially zero on $NonFOMC$ days and do not vary across portfolios. In contrast, the bottom (top) line indicates that turnovers in the stock market are below (above) their past monthly average before (after) FOMC announcements.

More interestingly, on $PreFOMC$ and $PostFOMC$ days, individual abnormal turnovers are related to market betas. The portfolio with a market beta of 0.5 are traded 1% less than its past monthly average on $PreFOMC$ trading days. In comparison, the portfolio with a market beta of 1.5 are traded about 3% less than its past monthly average. The relation between abnormal turnover and market betas is reversed on days after FOMC announcements. After FOMC announcements, the portfolio with a market beta of 0.5 are traded 12% more than its past monthly average; while the one with a market beta of 1.5 are traded about 15% more than its past monthly average. It is also worth to mention that the level of abnormal turnover on $PostFOMC$ days is much higher than the absolute level of the abnormal turnover on $PreFOMC$ days, which might be attributed to algorithm tradings who trade upon macroeconomic news releases (Scholtus, Van Dijk and Frijns (2014)) or differences-of-opinions on public signal (Kim and Verrecchia (1991), Kandel and Pearson (1995), Bollerslev, Li and Xue (2018)). Nevertheless, slopes of the top and bottom lines are similar, implying that the cross-sectional difference in volume changes is likely to be attributed to the same factor—the postponement of discretionary liquidity tradings.

In order to formally test the statistical significance of the volume-beta relation, I regress the abnormal turnover of individual stock on their market beta and also interact it with event dummies. The regression equation is as follows:

$$\begin{aligned}\tau_d^i =& Intercept + \beta_d^i \times PreFOMC + \beta_d^i \times PostFOMC \\ &+ PreFOMC + PostFOMC + Controls + e_d^i,\end{aligned} \tag{34}$$

where $PreFOMC$ and $PostFOMC$ are two event dummies—$PreFOMC$ equals to one if day d is the 24-hour trading window *before* a scheduled FOMC announcement and zero otherwise; $PostFOMC$ equals to one if day d is the 24-hour trading window *after* a scheduled FOMC announcement and zero otherwise. Regressions also include various control variables that may affect individual abnormal turnovers, such as firm size, book-to-market ratio, average total return in the past year, monthly idiosyncratic risk, the average (log) turnover in the previous month, and the turnover and percentage return on the previous day. Column 1 in Table 7 estimates the cross-sectional average of abnormal turnover on $PreFOMC$ and $PostFOMC$ days.

In anticipation of FOMC announcements, the turnover of individual stocks on average decline by about 2.75% comparing with its past monthly average level. Following the announcements, turnovers are 10.29% higher comparing with its past monthly average level.

Coefficients on the interaction terms relate the abnormal turnover to an asset's systematic risk. In Column 2, the coefficient on the first interaction term is -1.309, which reveals a negative correlation between the abnormal turnover and an asset's systematic risk on $PreFOMC$ days. Turnovers of assets that are more exposed to the systematic risk experience a greater volume decline before scheduled FOMC announcements. To be more specific, a stock with a market beta of 1.5 experiences a 3.38% ($= 1.418 + 1.309 \times 1.5$) decline in turnover before FOMC announcements; while a stock with a market beta of 0.5 only experiences a 2.07% ($= 1.418 + 1.309 \times 0.5$) decline in turnover at the same time. The coefficient on the second interaction term is 1.856, indicating that the correlation between abnormal turnover and systematic risk turns into a positive one on $PostFOMC$ days. The absolute difference in abnormal turnover between high-beta and low-beta assets on $PostFOMC$ days is similar to the one on $PreFOMC$ days. The greater volume changes among high-beta stocks around FOMC announcements is consistent with the prediction of Theorem 2.

6.2 Information asymmetries around FOMC announcements

Having documented volume dynamics in the stock market, in this section, I investigate the reason behind volume changes. If the volume dynamic around macroeconomic announcements is caused by discretionary liquidity tradings, this volume dynamic should be accompanied by changes in information environment, at both the market level or in the cross section.

Guided by Theorem 3, I estimate the price impact as the correlation between an incoming buy or sell order and the subsequent price changes. To this end, I first construct the signed order flow for each stock i on day d:

$$Signed\ Order\ Flow_d^i = Buys_d^i - Sells_d^i, \tag{35}$$

where $Buys_d^i$ is the total number of buy shares and $Sells_d^i$ is the total number of sell shares on day d for stock i. On each day, each trade is signed to a buy or sell order according to the Lee and Ready (1991) convention [8]. Having calculating the total signed volume, I estimate the price impact λ based on the following regression:

$$r_d^i = \lambda SOF_d^i + controls + \epsilon_d^i, \tag{36}$$

where r_d^i is the percentage return of stock i on day d. For ease of interpretation, I divide the total signed volume by the number of outstanding shares and denote the percentage ratio as SOF_d^i. With this construction, the estimated coefficient in equation 36 is easy to interpret—it equals to the percentage price change caused by transacting 1% of the firm's total outstanding shares. In order to control for variations in returns caused by factors that are unrelated to order flows, I also add standard firm characteristics to the regression.

To compare price impacts before and after FOMC announcements, I first estimate equation 36 daily using the cross section of all firms in the spirit of Fama and MacBeth (1973). Table 8 shows the average price impact by four subsamples sorted by the number of days elapsed since FOMC announcements occurred. Within each subsample, I compute the coefficient estimate (and standard error) as the time series average (and standard error) of the daily cross-sectional regression coefficients. In each regression, I also include variables that may affect information asymmetries as independent variables.

The first row reports the average price impact estimated from daily cross-sectional regressions with all stocks included. The average price impact in the week prior to FOMC announcements is about 2.308%. It increases to 2.600% on $PreFOMC$ days and then decreases to 2.098% on $PostFOMC$ days. In the week after FOMC announcements, the average price impact returns to 2.263%. The post-pre difference in price impact is about 0.502% (= 2.600% − 2.098%) and is statistically significant at 1% level. The 0.502% difference in price impact implies that a buyer-initiated trade of 1% of a firm's shares outstanding results in a 0.502% lower price

[8] A trade is a buy (sell) if the trade price is greater (less) than NBBO midpoint. A tick test is used if the trade price and NBBO midpoint equal. The tick test specifies that a trade is a buy (sell) if the most recent prior trade at a different price was at a lower (higher) price than the current trade price.

impact on $PostFOMC$ days than on $PreFOMC$ days. The decline of 0.502% is 19.30% of the 2.600% on $PreFOMC$ days.

The second and third rows in Table 8 also allow for comparison of price impact across stocks with different systematic risks. The second row reports the average price impact estimated from daily cross-sectional regressions with only stocks in the bottom beta quintile group. The result shows that stocks with low systematic risks experience a 10.24% ($= 2.063/2.301 - 1$) drop in price impact upon the arrival of FOMC announcements. In contrast, the third row shows that stocks in the top beta quintile group experience a 26.33% ($= 2.090/2.837 - 1$) drop in price impact upon the arrival of FOMC announcements. The decline in price impact among high-beta stocks are statistically significant at the 5% significance level. The post-pre change in price impact among high-beta stocks is also significantly greater than the one among low-beta stocks.

To conclude, the stock market experience a temporary information shock prior to FOMC announcements. A certain group of investors are informed of the incoming FOMC announcements before they are publicly announced. As a result, in the cross section, the increase in price impact is greater for assets with a higher systematic risk than those with a lower systematic risk. The change in information environment around FOMC announcements is consistent with the prediction of Theorem 3.

6.3 Volume dynamics around other macroeconomic announcements

Having established the volume dynamics in the stock market around FOMC announcements, I extend the analysis to two other major macroeconomic announcements—the scheduled releases of manufacturing purchase index (PMI) and Non-Farm Payroll statistics (NFP). They are used by investors as leading indicators of economic health, given their insight into sales, employment, inventory, and pricing. Moreover, because they are often the first major surveys released in each month, both are among the most highly watched economic indicators.

Figure 7 shows the abnormal turnover of SPDR surrounding the release of PMI (top panel) and NFP (bottom panel). According to the graph, there is no clear evidence that investors trade less before the release of these economic indicators. After the release of PMI or NFP, volumes skyrocket for a short period before returning to the normal level. To further test the statistical significance, I construct the abnormal turnover of SPDR, τ_c, following equation 1 but with log turnovers on each calendar day c. Then I regress the daily abnormal turnover on event dummies—*PreFOMC (PrePMI, PreNFP)* equals to one if a scheduled *FOMC (PMI, Non-Farm Payroll)* announcement occurs on calendar day $c+1$ and zero otherwise; *FOMC (PMI, NFP)* equals to one if a scheduled *FOMC (PMI, Non-Farm Payroll)* announcement occurs on calendar day c and zero otherwise.

Table 9 reports the regression results. The turnover of SPDR declines by about 5.18% on the calendar day before FOMC announcements and increases by 22.18% on the calendar day with FOMC announcements, comparing with the past monthly average. This turnover dynamic exhibits a pattern that is similar to the 2pm-2pm turnover dynamic in Table 4, with a smaller magnitude.

Columns 2–5 reports the regression results with dummies related to the release of PMI and NFP. Both the coefficients on $PrePMI$ and $PreNFP$ are insignificant. This result suggests that investors in general do not hold their tradings on days before the release of PMI or NFP. Nevertheless, coefficients on PMI and NFP are both positive and statistically significant. The turnover of SPDR increases by over 4.27% on days with PMI release. According to the top panel in Figure 7, the post-release increase in turnover is transient. It is only concentrated within the first half an hour after the PMI release. Similarly, the turnover of SPDR increases by over 7.88% on days with NFP release. This increase in turnover also only lasts for several trading hours, as is showed in the bottom panel in Figure 7.

To conclude this section, the stock market exhibits a "calm before the storm" effect only in anticipation of FOMC announcements, not other types of macroeconomic announcements. Nevertheless, the stock market experience a transient volume spike after the release of all three types macroeconomic announcements. One possible reason is that crowded algorithm tradings based on macroeconomic news cause an enormous increase in trading volume upon the arrival of macroeconomic news. Another possible explanation of the post-announcement turnover spike is that investors process public signals differently (Kim and Verrecchia (1991), Kim and

Verrecchia (1994), Kandel and Pearson (1995)). I discuss disagreement models as an alternative explanation for the volume dynamics around FOMC announcements in the following section.

7 Discussions

In this section, I discuss alternative theories to explain the volume dynamics around FOMC announcements. They are a story related to the early resolution of uncertainty, a story related to differences-of-opinions, and a story related to institutional ownership.

7.1 Early resolution of uncertainties

A growing body of literature investigates whether aggregate uncertainties have been resolved before the announcement of macroeconomic news and therefore contribute to the pre-announcement price drift (Hu et al. (2019)). Given that media coverage of macroeconomic announcements is prevalent nowadays, it is possible that economists perfectly learn monetary policy decisions through media (Lucca and Moench (2015)) or informal communications (Vissing-Jorgensen (2020)) before public announcements.

Nevertheless, it is unlikely that liquidity traders also learn such information before announcements. Otherwise, market makers should face less inventory risks and tend to provide more liquidity. As a consequence, trading volumes should increase in anticipation of announcements, rather than decrease. The early resolution of uncertainty for all investors therefore implies an increase in trading volumes and decrease in price impact before announcements, which is inconsistent with the volume dynamics in Table 4 and the price impact evidence in Table 8.

Public information can be costly to process (Engelberg (2008)). Therefore, it is possible that only agents who prefer earlier resolutions of uncertainties acquire information in anticipation of macroeconomic announcements. The differential timings of information acquisition between "early" learners and "late" learners might lead to information asymmetries that are similar to the one caused by information leakages.

7.2 Disagreement

Macroeconomic announcements, among various types of public news, can also be noisy (Kim and Verrecchia (1991)), and raise investors' disagreement on how news will affect firms' fundamental values. Upon the arrival of macroeconomic announcements, it is therefore very likely that investors agree to disagree on their interpretations of the same public signal (Harrison and Kreps (1978), Harris and Raviv (1993), Kandel and Pearson (1995), Scheinkman and Xiong (2003), Banerjee and Kremer (2010)). Because "differences-in-opinions" generates extra trading motives in absence of price changes, this type of models predicts a decline in the correlation between volume and volatility after the announcement of public signals.

However, the information asymmetry models, such as the one in section 5 or similar models (Llorente et al. (2002),Tetlock (2010)), predict that the correlation between volume and volatility increases after the announcement of public signals. The reason is that public signals resolve information asymmetries, motivating uninformed liquidity traders to facilitate the absorption of the persistent liquidity shock from informed investors after announcements.

In order to distinguish these two channels, I ask if the correlation between volume and volatility has changed upon the arrival of FOMC announcements. To answer this, I estimate the correlation between abnormal turnover and volatility using daily cross-sectional regressions:

$$\tau^i_d = \rho ln(|Ret|^i_d) + Controls^i_d + \epsilon^i_d, \tag{37}$$

where τ^i_d is the monthly detrended log turnover and $|Ret|^i_d$ is the absolute return on day d for firm i. The cross-sectional regressions also include market beta, firm size, annual return momentum, monthly idiosyncratic risk, and annual Amihud illiquidity to control for the cross-sectional variation in abnormal turnover caused by the variation in firm characteristics.

In order to control for other variables aside from information asymmetry that could affect the correlation between volume and volatility, I compare the time series average of estimated coefficients in the week before FOMC announcements($[t-5, t-1]$), on announcement days ($PostFOMC$), and the week after announcements ($[t+1, t+5]$), respectively. Table 10 reports estimation results for each subsample. The estimated coefficient on $ln(|Ret|)$ is 0.079 in the first column. This result indicates that in the week prior to FOMC announcements, 1% increase in absolute return is associated with 7.9% increase in turnover. In contrast, the estimated volume-volatility correlation is 0.087 on days with FOMC announcements, implying that 1% increase in absolute return is associated with 8.7% increase in turnover on these days. In the week after FOMC announcements, the correlation between volume and volatility returns to 0.074. The last two columns shows that the volume-volatility correlation on $PostFOMC$ days is significant higher than the average value in either the week before or the week after announcements.

To conclude, results in Table 10 imply that the correlation between volume and volatility has significantly increased after the arrival of FOMC announcements. This evidence is inconsistent with the "differences-in-opinions" theory, which predicts a decline in the correlation between volume and volatility after the arrival of public signals. Instead, the increased volume-volatility correlation is consistent with the prediction of information asymmetry models. Monetary policy announcements seem to resolve information asymmetries and facilitate the absorption of the persistent liquidity shock from informed investors.

7.3 Number of institutional investors

In the model, I assume that the total number of discretionary liquidity traders is constant. However, it might not be the case in the real world. Many institutional investors, such as mutual funds and pension funds, overweight high-beta assets (Frazzini and Pedersen (2014)). They usually have to rebalance their positions following a predetermined investment strategy (i.e. exogenous liquidity demands), instead of taking advantage of private information. When this type of investors participate in the market, they trade in a similar fashion to discretionary liquidity traders described by Admati and Pfleiderer (1988). Given that high-beta stocks are more widely held by these investors, these stocks are more prone to strategic liquidity trading. It is likely that the volume-beta correlation around FOMC announcements is attributed to the different distribution of liquidity traders among low-beta and high-beta assets, rather than the asset's exposure to the aggregate economy.

In this section, I investigate if the volume-beta correlation can be explained by the distribution of discretionary liquidity traders. Nevertheless, the total number of discretionary liquidity traders in a market is unobservable. Therefore, I use proxies to measure the number of discretionary liquidity traders. The first proxy to use is the total number of $13F$ institutional owners in the market. $13F$ institutional owners are institutional investors with at least \$100 million in assets under management. They are required by the Securities and Exchange Commission's (SEC) to disclose their equity holdings according to Form 13F quarterly. By using this proxy, I assume that the number of discretionary liquidity traders is positively correlated with the number of $13F$ institutional owners. To ensure that only past information is involved, the number of $13F$ institutional investors from the previous quarter is used.

Secondly, I use the annual Amihud illiquidity of an asset as the second proxy for the number of discretionary liquidity traders. By using this proxy, the underlying assumption is that a liquid market is likely to have more liquidity traders and henceforth also more discretionary ones. I measure the annual Amihud illiquidity of an asset by using the average ratio between daily absolute returns and dollar volumes over the past year.

Table 11 reports results from regressing abnormal turnover on the standardized number of $13F$ institutional owners. The estimated coefficient on the first interaction term negative, indicating that firms with more $13F$ institutional owners are likely to experience a greater "calm before storm" effect than firms with fewer $13F$ institutional owners. However, the coefficient is insignificant. After FOMC announcements, assets with more $13F$ institutional owners experience a greater volume increase than assets with fewer $13F$ investors. Nevertheless, Column 2 shows that the volume-beta correlation around FOMC announcements can not be explained the number of $13F$ institutional owners.

A more liquid market might attract more discretionary liquidity traders. As a result, Amihud illiquidity should be negatively correlated with the number of discretionary liquidity traders in the market. In Column 3, I regress the abnormal turnover on an asset's annual Amihud illiquidity. Coefficients on the interaction terms capture the cross-sectional difference in abnormal turnover among liquid and illiquid assets. The coefficient on $PreFOMC \times Amihud$ is positive, implying that assets with more discretionary liquidity traders (low Amihud) experience a greater volume decline in anticipation of FOMC announcements. These assets also experience greater volume increase after announcements. However, Column 4 shows that the volume-beta correlation around FOMC announcements can not be explained the number of discretionary liquidity traders proxied by Amihud illiquidity.

To conclude, the cross-sectional difference in abnormal turnovers among high-beta and low-beta assets is unlikely to attribute to the distribution of discretionary liquidity traders in different markets. The volume change in high-beta assets is greater than the one in low-beta assets because the former group of assets is more exposed to the macroeconomic risk.

8 Alternative measures of abnormal trading activities

In order to analyze the abnormal trading activities around macroeconomic announcements, I use log turnover detrended by its past monthly average to ensure that the time series is stationary. In this section, I show that the volume dynamics documented in the empirical section is robust when alternative volume measures or detrended methods are used.

In Table 12, I use various measures of trading activities as dependent variables and compare their values on $Pre(-Post)\ FOMC$ days with non-announcement days. To serve as a benchmark case, I first regress percentage abnormal turnover on FOMC dummy variables and report estimation results in Column 1. The estimated coefficient from this benchmark case indicates that individual turnovers on average decline by 1.23% before FOMC announcements and increase by 13.66% afterwards. Using the abnormal dollar volume (Column 2) or the abnormal share volume (Column 3) as dependent variables provides very similar estimates. In Column 4, the dependent variable is the individual log turnover, detrended by its average level over the previous year. This detrend window is initially used in Campbell, Grossman and Wang (1993). The annually detrended provides a slightly smaller $PreFOMC$ estimate and a larger $PostFOMC$ estimate.

In the last column, I use the level of individual turnovers as the dependent variable. Because turnover levels are persistent, I add its lagged value an additional independent variable to the regression. The regression result suggests that the level of turnover is below the sample average by 0.164 on $PreFOMC$ days, and it almost doubles the sample average after announcements. However, as is aforementioned, because the level of turnover is not a stationary process, residuals from this regression are prone to autocorrelations and OLS estimators are no longer efficient.

Having established the validity of abnormal turnover in measuring market trading activities, I investigate if various volume measures provide similar results in the cross section as well. The first column in Table 13 repeats the same column in in Table 7, to serve as a baseline case. From Column 2 to Column 3, I use the abnormal dollar volume, abnormal share volume and annually-detrend log turnover as dependent variables in the regression, respectively. The estimated coefficients on the interaction terms are not significantly different from the ones reported in the first column. However, using the level of turnover as the dependent variable results in much weaker results.

9 Alternative measures of price impact

In this section, I use Amihud illiquidity to show that the price impact significantly decline after macroeconomic announcements, consistent with prediction from Theorem 3 and evidence from section 6.2.

On each day d, I construct the Amihud illiquidity of each stock as the average ratio between absolute return and dollar volume (in millions) in each 5-minute interval. The Amihud illiquidity measure is both highly persistent and positively skewed. Therefore, I use the daily change in log Amihud illiquidity to examine the percent change in an asset's illiquidity around FOMC announcements, denoted as $\Delta ln(Amihud)$. I regress $\Delta ln(Amihud)$ on the event dummy $PostFOMC$. Column 1 in Table 14 shows that the estimated coefficient on $PostFOMC$ is -0.008, indicating that the illiquidity of trading S&P 500 stocks declines by 0.8% due to the arrival of FOMC announcements. Moreover, the decline in illiquidity around FOMC announcements is more profound for stocks with higher systematic risks. When market beta enters the regression, Column 2 in Table 14 shows that the coefficient on $PostFOMC$ turns into positive and insignificant. At the same time, the coefficient on the interaction term between $PostFOMC$ and $Beta$ is negative. This result implies that the decline of illiquidity around FOMC announcements is mainly driven by an asset's correlation with the aggregate economy, which is consistent with prediction of Theorem 3. More specifically, the coefficient on the interaction term indicates that firms with a market beta of 2 units experiences a 1.4% higher post-announcement change in illiquidity than firms with a market beta of 1 unit. Columns 3-5 show that the liquidity-beta relation is robust to the inclusion of standard firm characteristics or stocks' long-term illiquidity.

10 Conclusion

This paper investigates volume dynamics in the financial market around macroeconomic announcements. I find trading activities in the stock market measured by turnovers significantly decrease in anticipation of scheduled FOMC announcements and increase afterwards. The volume dynamic around macroeconomic announcements is consistent with the prediction of a rational expectation equilibrium model with private information and discretionary liquidity traders. A public signal about the economic state is revealed by macroeconomic announcements. At the same time, a certain group of traders who have superior information-processing abilities can receive the signal before it is publicly announced. Liquidity traders who can choose the optimal timing to satisfy their exogenous liquidity demands will prefer to trade after this public signal is announced.

This model not only explains the volume dynamics in the aggregate market but also has predictions in the cross section. Assets that are more exposed to the macroeconomic risk are also more exposed to information asymmetries caused by macroeconomic announcements. As a result, discretionary liquidity traders in the market with a higher systematic risk are more incentivied to hold their liquidity demands until the macroeconomic signal is publicly announced. Consistent with the model's prediction, I show that the volume change around FOMC announcements is more profound for high-beta assets than for low-beta assets. Moreover, the volume change is also accompanied by changes in information asymmetries. High-beta assets experience both a greater increase in price impact in anticipation of FOMC announcements and a greater decline in price impact afterwards, than low-beta assets.

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Table 1: **Scheduled release times of macroeconomics news** This table lists the scheduled release time (in Eastern Time) of different types of macroeconomic announcements in the sample period 1994–2018. The last column also shows the number of scheduled announcements every year.

Announcement yype	Scheduled time	Valid period	Number of ann. (per year)
FOMC statement	2:15 pm 12:30 pm 2:00 pm	Sep. 1994–Mar. 2011 Apr. 2011–Dec. 2012 Jan. 2013–Dec. 2018	8 8 8
FOMC press conference	2:15 pm 2:30 pm	Apr. 2011–Dec. 2012 Jan. 2013–Dec. 2018	4 4
PMI	10:00 am	Jan. 1996–Dec. 2018	12
Employment statistics	8:30 am	Jan. 1994–Dec. 2018	12

Table 2: **Summary statistics** This table reports summary statistics for SDPR for pre-(post-) FOMC 24-hour windows and for all other time in the sample period from September 1994 to May 2018. All variables except for $Shares\ outstanding$ are constructed from 2 p.m. on calendar date $t-1$ to 2 p.m. on calendar date t. Ret(%) is the percentage raw return of SPDR. $Turnover$ is the turnover volume of SPDR, defined as the ratio between total number of shares traded and total number of shares outstanding. $Share\ volume$ is the total number of shares traded in millions. $Dollar\ volume$ is the total amount of dollar transactions in millions. $Share\ outstanding$ is the total number of outstanding shares in millions on calendar date t. There are 189 FOMC announcements in the sample period. One post-FOMC 24-hour window is missing for the July 3rd, 1996 FOMC announcement because the following day is an official holiday.

	Mean	St. Dev.	P25	P50	P75	No. Obs.
			Panel A: NonFOMC			
Ret(%)	0.02	0.92	-0.39	0.04	0.48	5602
|Ret| (%)	0.64	0.66	0.19	0.44	0.86	5602
Turnover	193.70	166.11	85.34	138.20	250.54	5602
Share volume	76.91	82.49	15.54	54.73	104.92	5602
Dollar volume	10525.75	10121.55	1951.02	7858.29	16153.41	5602
Shares outstanding	471.93	342.01	102.67	445.87	776.88	5602
			Panel B: PreFOMC			
Ret(%)	0.29	0.65	-0.06	0.18	0.57	189
|Ret| (%)	0.48	0.52	0.12	0.33	0.62	189
Turnover	164.68	137.08	70.71	118.19	231.38	189
Share volume	68.25	80.07	12.76	47.75	92.03	189
Dollar volume	9297.83	9476.95	1743.97	6478.35	14212.33	189
Shares outstanding	473.03	341.26	149.42	449.97	776.88	189
			Panel C: PostFOMC			
Ret(%)	-0.00	1.04	-0.42	0.05	0.57	188
|Ret| (%)	0.74	0.73	0.19	0.49	1.06	188
Turnover	260.18	198.09	126.62	201.40	355.93	188
Share volume	110.59	112.12	21.67	81.12	156.76	188
Dollar volume	15379.63	14304.26	2753.84	11510.17	24202.82	188
Shares outstanding	475.37	341.04	149.42	445.08	792.53	188

Table 3: **Summary statistics** This table reports summary statistics for S&P 500 stocks in the sample period from September 1994 to May 2018. Variables in Panel A are constructed for each individual stock from 2 p.m. on calendar date $t-1$ to 2 p.m. on calendar date t. Ret(%) is the percentage raw return of individual stocks. $Turnover$ is the turnover volume, defined as the ratio between total number of shares traded and total number of shares outstanding. $Share\ volume$ is the total number of shares traded in millions. $Dollar\ volume$ is the total amount of dollar transactions in millions. $Signed\ volume$ is the total signed share volume in millions based on the Lee and Ready [1991] convention. Variables in Panel B represents for firm characteristics. Shares outstanding is the total number of outstanding shares on calendar date t. $Beta$ is the coefficient from one-year CAPM rolling regressions up to calendar date $t-1$. $Size$ is the market capitalization in millions on calendar date $t-1$. BM is the book-to-market ratio constructed following Gorodnichenko and Weber [2016]. $Momentum$ is the percentage cumulative return from day $t-225$ to date $t-1$. $IdioRisk$ is the volatility of the residual term from monthly CAPM rolling regressions up to calendar date $t-1$. $Amihud$ is the average annual ratio between absolute return and dollar volume, rescaled by multiplying 10^{10}. $Num.\ 13F\ owner$ is the total number of institution investors who are required to file Form 13F to the U.S. Securities and Exchange Commission, i.e. those with at least 100 million US dollars in assets under management.

	Mean	St. Dev.	P25	P50	P75	No. Obs.
Panel A: 2pm-2pm window						
Return (%)	0.02	1.88	-0.84	0.00	0.88	2142844
Turnover	6.75	10.20	2.58	4.42	7.74	2142844
Share volume	2.85	8.02	0.50	1.21	2.87	2142844
Dollar volume	113.46	198.09	20.48	55.50	128.34	2142844
Signed volume	0.06	0.65	-0.05	0.02	0.13	2142844
Panel B: Firm characteristics						
Shares outstanding	507.57	932.48	123.04	234.90	485.75	2142844
Beta	1.02	0.38	0.76	0.99	1.24	2142844
Size	0.23	0.41	0.05	0.10	0.23	2142844
BM	0.51	0.40	0.25	0.42	0.67	2142844
Momentum	0.14	0.36	-0.06	0.12	0.30	2142844
IdioRisk	1.60	0.78	1.06	1.41	1.93	2142844
Amihud	9.12	53.93	0.88	2.13	6.40	2142844
Num. 13F owner	481.08	309.44	274.00	390.00	593.00	1655220

Table 4: **Abnormal turnover of SPDR** This table shows regression coefficients of regressing the abnormal turnover of SPDR dummy variables: $\tau_d = PreFOMC + PostFOMC + Controls + e_d$. The dependent variable τ_d is the abnormal turnover in percent, defined as the log turnover of SPDR on day d, detrended by the its average value in the previous month. Main independent variables are two dummy variables—$PreFOMC$ equals to one if a scheduled FOMC announcement has been announced on day d and zero otherwise; $PostFOMC$ equals to one if a scheduled FOMC announcement has been announced on day $d-1$ and zero otherwise. Control variables are: percentage return on the previous day (Ret ($prev.\ day$)); turnover on the previous day ($Turnover$ ($prev.\ day$)); average turnover in the previous month ($Turnover$ ($prev.\ month$)); percentage absolute return on the previous day ($|Ret|$ ($prev.\ day$)); contemporaneous percentage absolute return($|Ret|$) . Values in parentheses are Newey and West [1987] standard errors robust to autocorrelations up to 5 daily lags. Regressions also include the $weekday$ fixed effect. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)
PreFOMC	-12.265***	-11.977***	-11.655***	-12.095***	-10.241***
	(2.725)	(2.664)	(2.556)	(2.695)	(2.464)
PostFOMC	28.132***	30.277***	32.837***	29.237***	33.448***
	(2.732)	(2.674)	(2.571)	(2.705)	(2.482)
Ret (prev. day)		-8.185***			-6.012***
		(0.496)			(0.463)
Turnover (prev. day)			146.113***		129.198***
			(5.434)		(5.324)
Turnover (prev. month)			-153.138***		-155.422***
			(6.376)		(6.214)
|Ret| (prev. day)				7.761***	4.869***
				(0.739)	(0.686)
|Ret|					9.108***
					(0.677)
R-sq	0.0213	0.0638	0.1386	0.0412	0.2009
N	5979	5978	5978	5978	5978

Table 5: **Volatility around FOMC announcements** This table reports estimated correlation between volume and volatility based on the following regression: $y_d = PreFOMC + PostFOMC + \tau_d + PreFOMC \times \tau_d + PostFOMC \times \tau_d + Controls + e_d$. In the left panel, the dependent variable y_d is the absolute percentage return of SPDR ($|Ret|$); in the right panel, the dependent variable is the log absolute return, detrended by its average value in the previous month, expressed in percent ($ln(|Ret|)$ $(detrended)$). In both panels, τ_d is the percentage abnormal turnover, defined as the log turnover of SPDR on day d, detrended by its average value in the previous month. $PreFOMC$ equals to one if a scheduled FOMC announcement has been announced on day d and zero otherwise; $PostFOMC$ equals to one if a scheduled FOMC announcement has been announced on day $d-1$ and zero otherwise. Values in parentheses are Newey and West [1987] standard errors robust to autocorrelations up to 5 daily lags. All regressions include the $weekday$ fixed effect. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	|Ret|		ln(|Ret|) (detrended)	
	(1)	(2)	(3)	(4)
PreFOMC	-0.131***	-0.115**	-28.823***	-22.390***
	(0.050)	(0.052)	(7.986)	(8.394)
PostFOMC	0.122**	0.019	16.051**	-1.321
	(0.050)	(0.068)	(8.029)	(10.844)
τ_d		0.003***		0.610***
		(0.000)		(0.038)
PreFOMC × τ_d		-0.002		-0.103
		(0.001)		(0.215)
PostFOMC × τ_d		0.000		0.012
		(0.002)		(0.244)
R-sq	0.0022	0.0349	0.0030	0.0460
N	5979	5979	5936	5936

Table 6: **The contemporaneous relation between volume and volatility** This table tests if volatility shocks explain volume changes in SPDR around FOMC announcements. To this end, I run the following regression: $\tau_d = PreFOMC + PostFOMC + x_d + PreFOMC \times x_d + PostFOMC \times x_d + Controls + e_d$. The dependent variable τ_d is the percentage abnormal turnover of SPDR, defined as the log turnover of SPDR on day d, detrended by the its average value in the previous month. x_d is either the absolute return of SPDR ($|Ret|$), or the monthly detrended log absolute return ($ln(|Ret|)$ $(detrended)$), both are expressed in percentage. $PreFOMC$ equals to one if a scheduled FOMC announcement has been announced on day d and zero otherwise; $PostFOMC$ equals to one if a scheduled FOMC announcement has been announced on day $d-1$ and zero otherwise. Values in parentheses are Newey and West [1987] standard errors robust to autocorrelations up to 5 daily lags. Regressions also include the $weekday$ fixed effect. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
PreFOMC	-12.265***	-10.431***	-11.126***	-9.774**
	(2.725)	(3.622)	(2.779)	(4.906)
PostFOMC	28.132***	29.017***	26.995***	26.702***
	(2.732)	(3.762)	(2.701)	(4.250)
|Ret|		9.924***		4.643***
		(0.751)		(1.025)
PreFOMC × |Ret|		-1.115		-2.012
		(5.069)		(6.898)
PostFOMC × |Ret|		-2.851		0.052
		(3.600)		(4.832)
ln(|Ret|) (detrended)			0.072***	0.053***
			(0.004)	(0.006)
PreFOMC × ln(|Ret|) (detrended)			-0.007	0.003
			(0.025)	(0.035)
PostFOMC × ln(|Ret|) (detrended)			-0.023	-0.025
			(0.024)	(0.032)
R-sq	0.0213	0.0531	0.0637	0.0679
N	5979	5979	5936	5936

Table 7: **Abnormal turnover and systematic risk** This table reports panel regressions of abnormal turnover (in percentage) on the interaction term between dummy variables and market beta: $\tau^i_d = PreFOMC + PostFOMC + PreFOMC \times Beta + PostFOMC \times Beta + Beta + Controls + e^i_d$. The dependent variable τ^i_d is the abnormal turnover of stock i on d; and the independent variable $Beta$ is the market beta of stock i, estimated from one-year rolling CAPM regressions up to day $d-1$. $PreFOMC$ is a dummy variable equal to one when a scheduled FOMC announcement has been released on day d and zero otherwise. $PostFOMC$ is equal to one when a scheduled FOMC announcement has been released on day $d-1$ and zero otherwise. Control variables include firm size ($Size$), book-to-market ratio (BM), annual return momentum ($Momentum$), monthly return idiosyncratic risk ($IdioRisk$), annual Amihud illiquidity ($Amihud$), monthly average log turnover ($ln(Turnover)$ $(prev.\ month)$), and lagged values of return (Ret $(prev.\ day)$), absolute return ($|Ret|$ $(prev.\ day)$) and turnover ($Turnover$ $(prev.\ day)$). Regressions also include the firm fixed effect and the weekday fixed effect. Values in parentheses are standard errors clustered by firms. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
PreFOMC	-2.747***	-1.418**	-1.410**	-1.360**	-1.492***	-1.383**
	(0.233)	(0.573)	(0.573)	(0.571)	(0.568)	(0.568)
PostFOMC	10.292***	8.406***	8.410***	8.503***	8.311***	8.649***
	(0.246)	(0.610)	(0.610)	(0.609)	(0.612)	(0.624)
PreFOMC × Beta		-1.309***	-1.316***	-1.294**	-1.394***	-1.359***
		(0.505)	(0.505)	(0.503)	(0.499)	(0.506)
PostFOMC × Beta		1.856***	1.855***	1.876***	2.187***	2.244***
		(0.559)	(0.559)	(0.558)	(0.567)	(0.584)
Beta		-0.175**	0.272***	0.870***	-2.605***	0.671
		(0.076)	(0.082)	(0.140)	(0.455)	(0.429)
Size			-0.892***			1.331**
			(0.124)			(0.576)
BM			1.166***			-0.656
			(0.135)			(0.855)
Momentum			-0.695***			-1.215***
			(0.084)			(0.266)
IdioRisk			-0.932***			-1.896***
			(0.043)			(0.365)
ln(Turnover) (prev. month)				-4.126***		-13.784***
				(0.118)		(2.001)
Turnover (prev. day)					0.874***	1.358***
					(0.165)	(0.317)
Ret (prev. day)					-0.811***	-0.792***
					(0.038)	(0.041)
R-sq	0.002	0.002	0.002	0.005	0.034	0.069
N	2142844	2142844	2142844	2142844	2142079	2142079

Table 8: **Price impact and systematic risk** This table reports estimated price impact from the following regression: $r_d^i = \lambda SOF_d^i + Controls_d^i + \epsilon_d^i$, where $Controls_d^i$ include the market beta ($Beta$), the firm size ($Size$), the book-to-market ratio (BM), annual return momentum ($Momentum$) and monthly return idiosyncratic risk ($IdioRisk$). The dependent variable r_d^i is the percentage return of firm i on day d; and the independent variable SOF_d^i is total signed volume in percentage of total number of shares outstanding. I estimate the regression equation daily using observations from the cross section. The point estimate in each row, from left to right, is the time series average of the daily regression coefficient in four different subsamples: the week before FOMC announcements ($[t-5, t-1]$), the day before FOMC announcements (t), the day after FOMC announcements ($t+1$), and the week after FOMC announcements ($[t+1, t+5]$). The post-pre difference is the estimated price impact on day $t+1$ minus the estimated price impact on day t. Values in parentheses are standard errors robust to heteroskedasticity and autocorrelations up to 5 daily lags (only Column 1 and Column 5). The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)
	$[t-5, t-1]$	t (PreFOMC day)	$t+1$ (PostFOMC day)	$[t+1, t+5]$	Post - Pre
Full sample	2.308***	2.600***	2.098***	2.263***	-0.502***
	(0.081)	(0.187)	(0.215)	(0.085)	(0.167)
Bottom quintile	2.242***	2.309***	2.063***	2.082***	-0.246
	(0.133)	(0.300)	(0.271)	(0.140)	(0.336)
Top quintile	2.656***	2.837***	2.090***	2.509***	-0.748**
	(0.152)	(0.319)	(0.304)	(0.153)	(0.361)

Table 9: **Abnormal turnover of SPDR around other macroeconomic announcements** This table shows estimated coefficients of regressing the abnormal turnover of SPDR on various macroeconomic announcements dummies: $\tau_c = PreFOMC + FOMC + PrePMI + PMI + PreNFP + NFP + Controls + e_d$. The dependent variable τ_c is the daily percentage abnormal turnover, defined as the log turnover of SPDR on calendar day c, detrended by the its average value in the previous month. $PreFOMC$ ($PrePMI$, $PreNFP$) equals to one if a scheduled FOMC (PMI, Non-Farm Payroll) announcement occurs on calendar day $c+1$ and zero otherwise; $FOMC$ (PMI, NFP) equals to one if a scheduled FOMC (PMI, Non-Farm Payroll) announcement occurs on calendar day c and zero otherwise. Control variables are: percentage return on the previous day (Ret ($prev.\ day$)); turnover on the previous day ($Turnover$ ($prev.\ day$)); average turnover in the previous month ($Turnover$ ($prev.\ month$)); contemporaneous absolute percentage return ($|Ret|$). Values in parentheses are the standard errors of point estimates clustered by $weekday$ groups. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)
PreFOMC	-5.18**			-6.28**	-4.84*
	(2.50)			(2.63)	(2.52)
FOMC	22.18***			19.78***	22.57***
	(2.29)			(2.40)	(2.32)
PrePMI		1.02		0.98	0.96
		(2.00)		(2.07)	(1.94)
PMI		4.27**		4.97**	4.31**
		(2.09)		(2.17)	(2.10)
PreNFP			-0.17	-0.06	-0.21
			(2.05)	(2.22)	(2.07)
NFP			7.88***	8.36***	8.35***
			(2.09)	(2.22)	(2.11)
Ret (prev. day)	-6.46***	-6.35***	-6.36***		-6.42***
	(0.50)	(0.50)	(0.50)		(0.50)
Turnover (prev. day)	0.11***	0.10***	0.10***		0.11***
	(0.01)	(0.01)	(0.01)		(0.01)
Turnover (prev. month)	-0.12***	-0.12***	-0.12***		-0.12***
	(0.01)	(0.01)	(0.01)		(0.01)
|Ret|	5.03***	5.09***	5.09***		5.05***
	(0.78)	(0.79)	(0.79)		(0.78)
Constant	-0.39	-0.09	-0.25	-0.99	-1.02
	(1.12)	(1.15)	(1.14)	(0.85)	(1.17)
R-sq	0.1149	0.1046	0.1060	0.0117	0.1176
N	5978	5978	5978	5979	5978

Table 10: **Volume volatility correlation** This table reports the time series average of the daily cross-sectional regression based on equation 37 in the text: $\tau_d^i = \rho ln(|Ret|_d^i) + Controls_d^i + \epsilon_d^i$. The dependent variable τ_d^i is the monthly detrended log turnover and $|Ret|_d^i$ is the absolute return on day d for firm i. Control variables include market beta ($Beta$), firm size ($Size$), book-to-market ratio (BM), annual return momentum ($Momentum$), monthly idiosyncratic risk ($IdioRisk$) and annual Amihud illiquidity ($Amihud$). The point estimate in each column, from left to right, is the time series average of the daily regression coefficient in three different subsamples: the week before FOMC announcements ($[t-5, t-1]$), the day after FOMC announcements ($PostFOMC$), and the week after FOMC announcements ($[t+1, t+5]$). The forth column reports the difference between the volume-volatiliy correlation on $PostFOMC$ days and the value in the pre-announcement week. The fifth column reports the difference between the volume-volatiliy correlation on $PostFOMC$ days and the value in the post-announcement week. Values in parentheses are standard errors robust to heteroskedasticity and autocorrelations up to 5 daily lags (only Column 1 and Column 3). The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1) [t-5, t-1]	(2) PostFOMC	(3) [t+1, t+5]	(2) - (1)	(2) - (3)
ln(|Ret|)	0.079***	0.087***	0.074***	0.008***	0.013 ***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Beta	-0.018***	0.022***	-0.013***		
	(0.004)	(0.007)	(0.004)		
Size	-0.002	-0.000	-0.003		
	(0.003)	(0.005)	(0.004)		
BM	-0.005	0.015**	0.010***		
	(0.004)	(0.006)	(0.003)		
Momentum	-0.012***	-0.001	-0.006		
	(0.005)	(0.007)	(0.004)		
IdioRisk	-0.040***	-0.068***	-0.042***		
	(0.003)	(0.005)	(0.003)		
Amihud (prev. year)	0.003***	0.000	0.002***		
	(0.001)	(0.001)	(0.001)		
Constant	0.490***	0.622***	0.442***		
	(0.015)	(0.022)	(0.014)		
R-sq	0.110	0.102	0.098		
N	328141	65427	326505		

Table 11: **Discretionary liquidity traders** This table reports panel regressions of abnormal turnover (in percentage) on interaction terms between FOMC-related dummies and market beta, and between FOMC-related dummies and number of discretionary liquidity traders: $\tau_d^i = PreFOMC + PostFOMC + PreFOMC \times l_d^i + PostFOMC \times l_d^i + l_d^i + PreFOMC \times Beta + PostFOMC \times Beta + Beta + Controls + e_d^i$. The dependent variable τ_d^i is the abnormal turnover of stock i on d; and the main independent variables are l_d^i, the number of discretionary liquidity traders measured either by the (standardized) number of $13F$ institutional owners from the previous quarter ($Num.\ 13F\ owner$) or by the (inverse of) annually average ratio between daily absolute return and dollar volume ($Amihud$). $13F$ institutional owners are institutional investors with at least $100 million in assets under management. They are required by the Securities and Exchange Commission's (SEC) to disclose their equity holdings according to Form 13F quarterly. $Beta$ is the market beta of stock i, estimated from one-year rolling CAPM regressions up to day $d-1$. $PreFOMC$ is a dummy variable equal to one when a scheduled FOMC announcement has been released on day d and zero otherwise. $PostFOMC$ is equal to one when a scheduled FOMC announcement has been released on day $d-1$ and zero otherwise. Control variables include firm size ($Size$), book-to-market ratio (BM), annual return momentum ($Momentum$), monthly return idiosyncratic risk ($IdioRisk$), annual Amihud illiquidity ($Amihud$), monthly average log turnover ($ln(Turnover)\ (prev.\ month)$), and lagged values of return ($Ret\ (prev.\ day)$), absolute return ($|Ret|\ (prev.\ day)$) and turnover ($Turnover\ (prev.\ day)$). Regressions also include the firm fixed effect and the weekday fixed effect. Values in parentheses are standard errors clustered by firms. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
PreFOMC	-3.153***	-2.075***	-3.173***	-1.712***	-3.721***	-2.638***
	(0.238)	(0.612)	(0.254)	(0.580)	(0.276)	(0.641)
PostFOMC	11.264***	7.764***	11.485***	9.102***	11.768***	8.257***
	(0.276)	(0.681)	(0.292)	(0.630)	(0.335)	(0.688)
PreFOMC × Num. 13F owner	-0.344	-0.382			0.111	0.073
	(0.238)	(0.238)			(0.268)	(0.269)
PostFOMC × Num. 13F owner	1.542***	1.663***			1.178***	1.297***
	(0.254)	(0.245)			(0.276)	(0.264)
PreFOMC × Amihud			0.067***	0.070***	0.094***	0.095***
			(0.022)	(0.022)	(0.027)	(0.027)
PostFOMC × Amihud			-0.086***	-0.091***	-0.079***	-0.079***
			(0.026)	(0.026)	(0.030)	(0.031)
PreFOMC × Beta		-1.060*		-1.454***		-1.066*
		(0.546)		(0.510)		(0.550)
PostFOMC × Beta		3.435***		2.371***		3.449***
		(0.616)		(0.580)		(0.613)
Num. 13F owner	3.504***	3.465***			3.150***	3.097***
	(0.414)	(0.425)			(0.393)	(0.404)
Beta		0.765		0.880**		0.989*
		(0.586)		(0.435)		(0.599)
Amihud			-0.262***	-0.264***	-0.247***	-0.249***
			(0.025)	(0.025)	(0.030)	(0.029)
R-sq	0.078	0.078	0.062	0.062	0.078	0.079
N	1654658	1654658	2142079	2142079	1654658	1654658

Table 12: **Abnormal volume measures** This table reports estimation results of regressing alternative volume measures on FOMC-related dummies: $v_d^i = PreFOMC + PostFOMC + e_d^i$. The dependent variable v_d^i is the volume measure for stock i on d. From left to right, the dependent variables in each regression is: monthly-detrended log dollar volume ($Ab.\ dvol$), monthly-detrended log share volume ($Ab.\ svol$), annually-detrended log turnover ($Ab.\ turnover(ann.detrend)$) and the level of turnover ($Turonver$). $PreFOMC$ is a dummy variable equal to one when a scheduled FOMC announcement has been released on day d and zero otherwise. $PostFOMC$ is equal to one when a scheduled FOMC announcement has been released on day $d-1$ and zero otherwise. Regressions also control for the firm fixed effect and the weekday fixed effect. Values in parentheses are standard errors clustered by firms. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
	Ab. dvol	Ab. svol	Ab. turnover (ann. detrend)	Turnover
PreFOMC	-2.638***	-2.746***	-1.277***	-0.164***
	(0.233)	(0.234)	(0.223)	(0.024)
PostFOMC	10.529***	10.292***	12.539***	0.999***
	(0.249)	(0.247)	(0.242)	(0.046)
Turnover (prev. day)				0.774***
				(0.013)
R-sq	0.002	0.002	0.002	0.599
N	2142844	2142844	2128217	2142079

Table 13: **Abnormal volume measures in the cross section** This table reports estimation results of regressing alternative volume measures on interaction terms between FOMC-related dummies and market betas: $v_d^i = PreFOMC \times Beta + PostFOMC \times Beta + PreFOMC + PostFOMC + e_d^i$. The dependent variable v_d^i is the volume measure for stock i on d. From left to right, the dependent variables in each regression is: monthly-detrended log dollar volume ($Ab.\ dvol$), monthly-detrended log share volume ($Ab.\ svol$), annually-detrended log turnover ($Ab.\ turnover(ann.detrend)$) and the level of turnover ($Turonver$). $PreFOMC$ is a dummy variable equal to one when a scheduled FOMC announcement has been released on day d and zero otherwise. $PostFOMC$ is equal to one when a scheduled FOMC announcement has been released on day $d-1$ and zero otherwise. Control variables include the market beta ($Beta$), the firm size($Size$), the book-to-market ratio (BM), annual return momentum ($Momentum$), monthly return idiosyncratic risk ($IdioRisk$), annual Amihud illiquidity ($Amihud$), monthly average turnover ($Turnover\ (prev.\ month)$), and lagged values of return ($Ret(prev.\ day)$), absolute return ($|Ret|\ (prev.\ day)$) and turnover ($Turnover\ (prev.\ day)$). Regressions also control for the firm fixed effect and the weekday fixed effect. Values in parentheses are standard errors clustered by firms. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1) Ab. dvol	(2) Ab. svol	(3) Ab. turnover (ann. detrend)	(4) Turnover
PreFOMC	-1.286**	-1.342**	-0.679	-0.126
	(0.565)	(0.567)	(0.564)	(0.084)
PostFOMC	8.827***	8.681***	9.893***	-0.438***
	(0.633)	(0.624)	(0.616)	(0.125)
PreFOMC × Beta	-1.362***	-1.401***	-1.087**	-0.054
	(0.503)	(0.505)	(0.500)	(0.085)
PostFOMC × Beta	2.069***	2.213***	2.498***	1.388***
	(0.596)	(0.584)	(0.581)	(0.141)
Beta	0.549	0.640	-4.091***	0.093
	(0.412)	(0.431)	(1.245)	(0.101)
Size	1.455**	1.266**	-9.802***	-0.254***
	(0.568)	(0.562)	(1.700)	(0.069)
BM	-1.786**	-1.006	-8.854***	0.833***
	(0.876)	(0.844)	(1.838)	(0.162)
Momentum	0.833***	-0.852***	-6.673***	0.084
	(0.251)	(0.269)	(0.971)	(0.071)
IdioRisk	-1.387***	-1.808***	-5.111***	0.263***
	(0.354)	(0.369)	(0.590)	(0.069)
ln(Turnover) (prev. month)	-13.457***	-13.724***	12.280***	1.865***
	(1.942)	(2.005)	(2.170)	(0.096)
Turnover (prev. day)	1.314***	1.354***	1.527***	0.701***
	(0.307)	(0.318)	(0.334)	(0.018)
Ret (prev. day)	0.091**	-0.796***	-0.718***	-0.105***
	(0.041)	(0.041)	(0.044)	(0.006)
R-sq	0.057	0.061	0.117	0.614
N	2142079	2142079	2127533	2142079

Table 14: **Changes in liquidity around FOMC announcements** This table reports results of panel regressions that investigate the change in liquidity upon the arrival of FOMC announcements. The regression is based on the following equation: $\Delta ln(Amihud)_d^i = PreFOMC + PostFOMC + + PreFOMC \times Beta + PostFOMC \times Beta + Beta + Controls + e_d^i$. The dependent variable ($\Delta ln(Amihud)_d^i$) in the regression is the daily change in the stock's (log) Amihud illiquidity; and the main independent variable is the interaction term between FOMC-related dummies and $Beta$ is the market beta of stock i, estimated from one-year rolling CAPM regressions up to day $d-1$. $PostFOMC$ is equal to one when a scheduled FOMC announcement has been released on day $d-1$ and zero otherwise. Control variables include firm size ($Size$), book-to-market ratio (BM), annual return momentum ($Momentum$), monthly return idiosyncratic risk ($IdioRisk$), monthly average log turnover ($ln(Turnover)$ $(prev.\ month)$) and annual (log) Amihud illiquidity ($log(Amihud)$ $(pre.\ year)$). Regressions also include the firm fixed effect and the weekday fixed effect. Values in parentheses are standard errors clustered by firms. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels. The sample period is September 1994–May 2018. The *, **, *** symbols denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)
PostFOMC × Beta		-0.014**	-0.014**	-0.014**	-0.014**
		(0.006)	(0.006)	(0.006)	(0.006)
PostFOMC	-0.008***	0.006	0.006	0.005	0.005
	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)
Beta		0.000	0.001**	-0.005***	-0.003***
		(0.000)	(0.000)	(0.001)	(0.001)
Size			0.003***		0.016***
			(0.000)		(0.003)
BM			-0.004***		-0.013***
			(0.001)		(0.001)
Momentum			-0.005***		-0.007***
			(0.000)		(0.000)
IdioRisk			0.001***		-0.007***
			(0.000)		(0.000)
ln(Turnover) (prev. month)				0.018***	0.025***
				(0.000)	(0.001)
ln(Amihud) (prev. year)				0.005***	0.011***
				(0.000)	(0.000)
R-sq	0.000	0.000	0.000	0.000	0.000
N	2142079	2142079	2142079	2142079	2142079

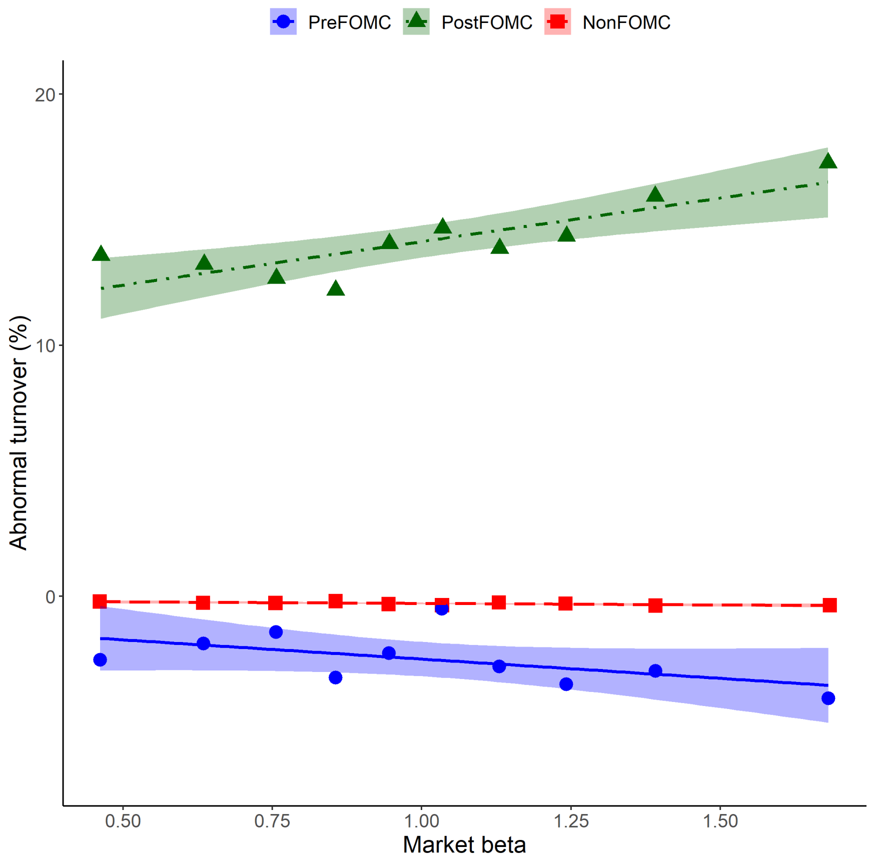

Figure 4: **Abnormal turnover of beta-sorted portfolios** This figure plots the average 2pm-to-2pm abnormal turnover (in percentage) against market betas for ten value-weighted beta-sorted portfolios on "PreFOMC", "PostFOMC" and "NonFOMC" days, respectively. "PreFOMC" represents for the 24 hours before scheduled FOMC announcements. "PostFOMC" represents for the 24 hours following FOMC announcements. "NonFOMC" are the rest of days in the sample. The beta deciles for sorting are calculated based on the distribution of estimated individual betas from the previous day. Market beta and abnormal turnover of portfolios are the value-weighted average of individual values within each decile group. For stock i on day d, abnormal turnover is the logarithm of the ratio of the total turnover to its average level in the previous month; market beta is estimated from a regression of daily excess stock returns on daily excess market returns using observations in the past 252 days. Individual assets only include S&P 500 stocks. Shaded areas are ordinary least squared estimates implied by the average portfolio abnormal turnover on each type of day. The sample covers the March 1994 to May 2018 period.

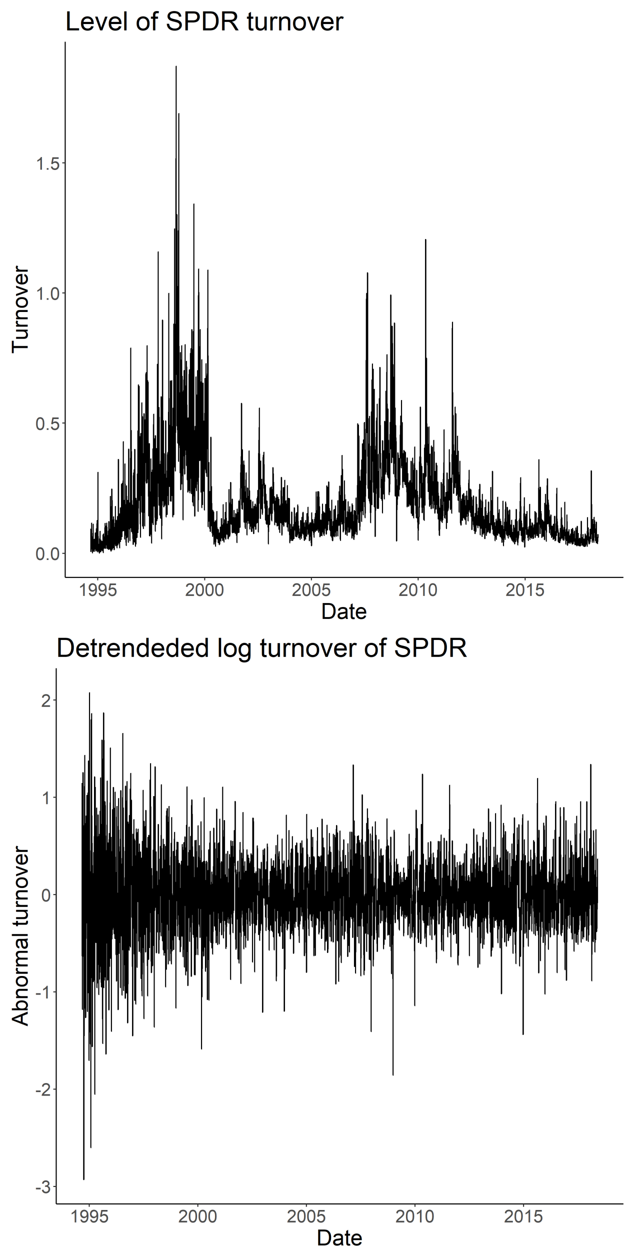

Figure 5: **Turnover of SPDR** This figure plots the turnover time series of SPDR spanning over the sample period March 1994—May 2018. The top chart plots the level of turnover and the bottom plots the monthly detrended log turnover.

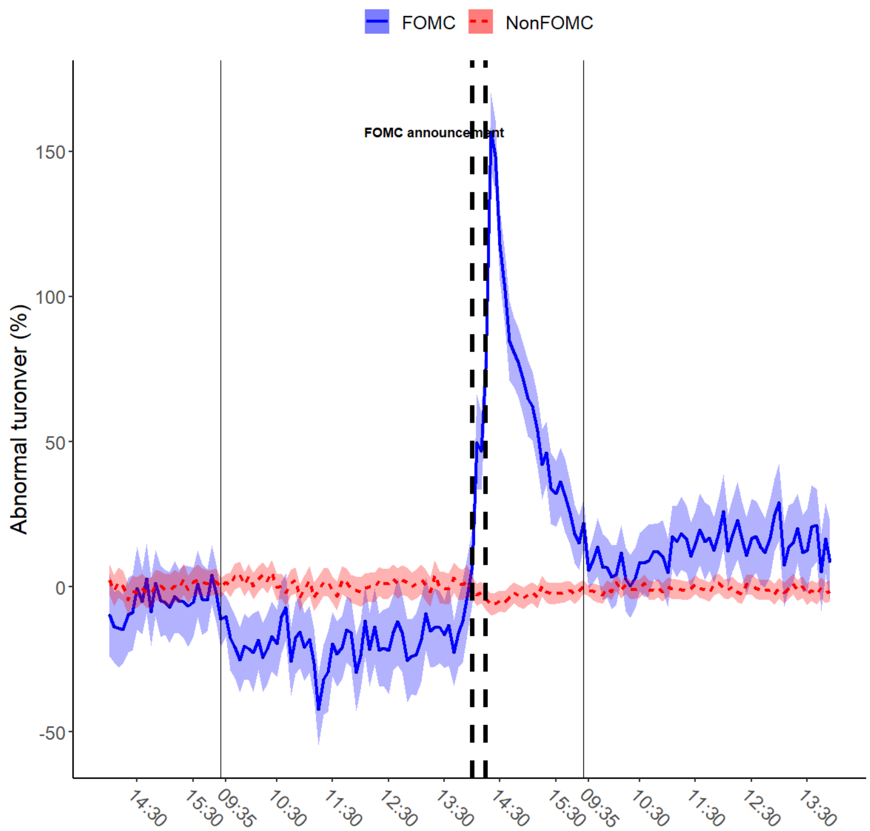

Figure 6: **Abnormal turnover of SPDR** This figure shows the average abnormal turnover of SPDR S&P 500 ETF (SPDR) for each 5-minutes trading window over day triplets. The abnormal turnover at time h is defined as the logarithm turnover at time h to its average level in the previous month. The blue solid line shows the average abnormal turnover from 2 p.m. on the day before a FOMC announcement to 2 p.m. on the day after a FOMC announcement. The dashed red line is the result of the same calculation for three-days windows surrounding 3000 dates randomly drawn from Non-FOMC announcement days. The shaded areas represent pointwise 95% confidence bands around average abnormal turnovers. The sample period is from September 1994 through May 2018. The dash-dotted vertical line, the dotted vertical line and the dashed vertical line, indicate 2 p.m. and 2:15 p.m., respectively.

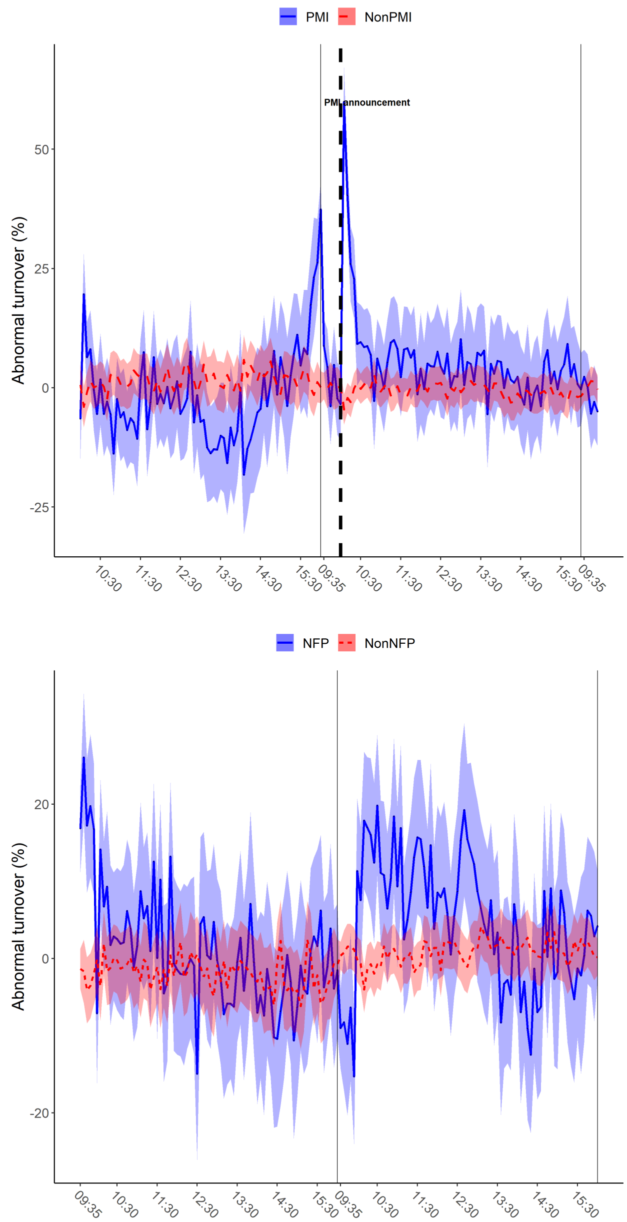

Figure 7: **Abnormal turnover of SPDR** This figure shows the average abnormal turnover of SPDR S&P 500 ETF (SPDR) by each five minutes around PMI announcements. The abnormal turnover at time h is defined as the logarithm turnover at time h to its average level in the previous month. The blue solid line shows the average abnormal turnover in 24 hours before and after scheduled PMI releases in the left panel and scheduled Non-Farm Payroll (i.e. NFP) releases in the right panel. In both panels, dashed red lines are the result of the same calculation for 48-hours windows surrounding 3000 dates randomly drawn from non-release days. The shaded areas represent pointwise 95% confidence bands around average abnormal turnovers. The sample period is from September 1994 through May 2018. The dash vertical line in the left panel is 10:00 a.m., which is typically the announcement of PMI index. The Non-Farm Payroll statistics is typically announced at 8:30 a.m. and is out of regular trading hours.

A Construction of control variables

Table 15: **Data sources and definitions of firm characteristics** This table lists the construction methodology of measures of firm characteristics and the source of the data.

Variables	Definition	Data Source
Beta	$= \frac{\sum_{k=1}^{225}(r_{i,d-k}-\bar{r}_i)(r_{m,d-k}-\bar{r}_m)}{\sum_{k=1}^{225}(r_{i,d-k}-\bar{r}_i)^2}$	Estimated from regressing the daily stock excess return $r_{i,d-k}$ on the daily market excess return $r_{m,d-k}$ over the past year. Daily stock returns (including dividends) are from *crsp*; daily market returns are the return of value-weighted market portfolio and risk-free rates are the one-month treasury rates. Both are from *Ken French's data library*.
IdioRisk		Defined as the standard deviation of the residual term from regressing the daily stock excess return $r_{i,d-k}$ on the daily market excess return $r_{m,d-k}$ over the previous month (i.e., $k = 1, 2, ..., 22$). Daily stock returns (including dividends) are from *crsp*; daily market returns and risk-free rates are from *Ken French's data library*.
Size	$= ln(p_{i,d} \times V_{i,d})$	Defined as the logarithm of the daily market capitalization in dollars. $p_{i,d}$ is the daily stock close price, and $V_{i,d}$ is the daily total share volume. Both are from *crsp*.

BM	$= ln(\frac{Book-value_{i,d}}{Market-value_{i,d}})$	Defined as the logarithm of the book-to-market ratio. $Book-value_{i,d}$ is the annual book value of firm i at the end of latest fiscal year from *compustat*, $Market-value_{i,d} = p_{i,d} \times V_{i,d}$ is the daily market capitalization in dollars.
Momentum	$= \frac{1}{225}\sum_{k=1}^{225} \tilde{r}_{i,d-k}$	Defined as the average daily stock returns in the past year (i.e., $k = 1, 2, ..., 252$). $\tilde{r}_{i,d-k}$ is the daily stock returns (including dividends) from *crsp*.
Amihud	$= ln(\frac{1}{225}\sum_{k=1}^{225} \frac{\lvert\tilde{r}_{i,d-k}\rvert}{p_{i,d} \times V_{i,d}})$	Defined as the natural logarithm of the average ratio between the daily absolute stock return and the daily dollar volume over the past year (i.e., $k = 1, 2, ..., 252$). Daily stock returns $\tilde{r}_{i,d-k}$, close prices $p_{i,d}$ and trading volumes $V_{i,d}$ are from *crsp*.
Turnover (last month)	$= ln(\frac{1}{22}\sum_{k=1}^{22} \frac{V_{i,d-k}}{shrout_{i,d-k}})$	Defined as the logarithm of the average ratio between end-of-day share volumes $V_{i,d-k}$ and total number of shares outstanding $shrout_{i,d-k}$ in the previous month (i.e., $k = 1, 2, ..., 252$). Data are from *crsp*.