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The role of intra-day volatility pattern in jump detection: Empirical evidence on how financial markets respond to macroeconomic news announcements

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Abstract

This paper examines the effect of adjusting for the intra-day volatility pattern on jump detection. Using tests that identify the intra-day timing of jumps, we show that before the adjustment, jumps in the financial market have high probability of occurring concurrently with pre-scheduled economy-wide news announcements. We demonstrate that adjustment for the U-shaped volatility pattern prior to jump detection effectively removes most of the association between jumps and macroeconomic news announcements. We find empirical evidence that only news that comes with large surprise can cause jumps in the market index after the volatility adjustment, while the effect of other types of news is largely absorbed through the continuous volatility channel. The FOMC meeting announcement is shown to have the highest association with jumps in the market both before and after the adjustment.

JEL: C58, C12, G14

Keywords: volatility pattern, intra-day jumps, news announcements, high frequency data

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1. Introduction

The volatility of financial asset returns often exhibits a distinct intra-day pattern. Similar to other financial variables such as trade volume, the return volatility exhibits a U-shaped pattern within a trading day, that is, higher levels of volatility around market opening and closing times than during the trading day (Andersen and Bollerslev, 1997; Andersen et al., 2001; Hecq et al., 2012). The existing literature attributes this intra-day pattern to the strategic interaction of traders around market opening and closing. The fact that macroeconomic news announcements can increase the volatility of asset returns has also been well documented in many studies (see, for example, Jones et al., 1998; Andersen and Bollerslev, 1998; Erdemlioglu et al., 2012, and references therein). As many macroeconomic news announcements are pre-scheduled on a regular basis, their impacts may be implicitly considered as being a part of the intra-day volatility pattern, that is, higher volatility at times when news is often announced.

More recent literature puts greater emphasis on the association between macroeconomic news announcements with large discontinuities in asset prices, which are commonly known as jumps in the high frequency financial econometrics literature.[1] Growing evidence suggests that separating jumps from the continuous price movements is beneficial for risk diversification and portfolio management (Todorov and Bollerslev, 2010). Barndorff-Nielsen and Shephard (2006), Lee and Mykland (2008) and Aït-Sahalia and Jacod (2012), amongst others, have developed a series of statistical procedures to detect jumps in a given price series. In practice, the presence of the intra-day volatility pattern may affect the outcome of these jump tests, and thus affect our assessment on how asset prices incorporate news information. Nevertheless there is little discussion in the literature as to whether and why we should adjust for this U-shaped intra-day volatility pattern.

[1] Prominent contributions in this area include Maheu and McCurdy (2004); Lahaye et al. (2011); Rangel (2011); Lee (2012); Erdemlioglu et al. (2012); Miao et al. (2013); Gilder et al. (2014) and Dewachter et al. (2014).

This paper examines the effect of adjusting for the intra-day volatility pattern on jump detection. We hypothesize that financial markets absorb the impact of new information arrival through two different channels: (i) elevated volatility of the continuous diffusive component of the price processes; (ii) large price disruptions that reflect rapid re-formation of the underlying expected values of the assets. US macroeconomic news announcements are taken as the source of the information arrival in our study because most of them are pre-scheduled on a regular basis. If our hypothesis holds, once the impacts of macro announcements are controlled for through the intra-day volatility pattern, we should rarely observe the occurrence of market jumps concurrently with macroeconomic news releases, unless the content of the news surprises the market. This provides a fresh perspective on how financial markets respond to the arrival of market-wide new information.

The contribution of this paper is twofold. Firstly, in the econometric aspect, we use a jump test both with and without the adjustment of the U-shaped volatility pattern, to demonstrate that the decision to adjust for the intra-day volatility pattern has substantial impact on the testing outcome of jumps, and hence should be applied with caution. We employ the univariate jump test proposed by Lee and Mykland (2008) (LM henceforth) to detect jumps in the market index and individual stocks. The intra-day volatility pattern is taken into account by using the robust-to-jumps volatility adjustment of Bollerslev et al. (2013). We find that the volatility-adjusted jump test leads to considerably fewer jumps and different timing of jumps, which is in line with the conclusion of Boudt and Petitjean (2014).

Secondly, we link the U-shaped intra-day volatility pattern to the timing of the scheduled macroeconomic news announcements, and explore the economic interpretation of the different testing outcomes of jumps before and after the volatility adjustment. Before the volatility adjustment, the most distinct feature of the detected jumps is that they are much more likely to occur at around 10 am and shortly after 2 pm compared with other time points during a trading day. Interestingly, this tendency disappears after the intra-day volatility pattern has been accounted for. Given the fact that the timing of these jumps coincides with the time of many scheduled macroeconomic news announcements in the US, we further explore the driving force of this phenomenon by linking these jumps to the regular release of macro news announcements. The results show that the Federal Open Market Committee (FOMC) meeting announcement released at 2:15 pm has the most influential impact on jumps in the financial markets. After adjusting for the intra-day volatility pattern, there are far fewer concurrent occurrences of market jumps and macro news releases. We conjecture that the impacts of many expected news announcements and news with mixed signals have been effectively absorbed into the volatility pattern, and hence only news that comes with large surprise will cause jumps in the financial market after volatility has been taken into account. To validate this hypothesis, we examine each individual case where a market jump occurs concurrently with a news announcement, and the market reactions support our reasoning in almost all cases.

The remainder of this paper is organized as follows. Section 2 introduces the modelling framework for estimating the intra-day volatility pattern and identifying jumps. Section 3 discusses the US stock market data that is used in this paper. Section 4 presents the empirical results on changes in market volatility and the characterization of intra-day jumps. Section 5 investigates the role of the intra-day volatility pattern and its association with scheduled macroeconomic news announcements. Section 6 concludes.

2. Methodology

The log-price of an asset p_t is assumed to follow a continuous-time jump diffusion process,

$$r_t \equiv \mathrm{d}p_t = \alpha_t \,\mathrm{d}t + \sigma_t \,\mathrm{d}W_t + \kappa_t \,\mathrm{d}\mu_t, \qquad t \in (0, T), \tag{1}$$

where α_t is the drift term, W_t is a standard Brownian motion, σ_t denotes the time-varying spot volatility, μ_t is a counting process for the discrete jump component, and $\kappa_t = p_t - p_{t-}$ denotes the size of the jump at time t. The usual quadratic variation for this process is defined as

$$QV_t = \int_0^t \sigma_s^2 \mathrm{d}s + \sum_{0<s\leq t} \kappa_s^2, \tag{2}$$

where $IV_t = \int_0^t \sigma_s^2 \mathrm{d}s$ denotes integrated volatility. Thus the total variation in a price process, QV_t, consists of the variation that comes from the continuous Brownian component IV_t, and the aggregation of squared jumps $\sum_{0<s\leq t} \kappa_s^2$.

In practice, instead of having a continuous record of the price process, we usually obtain discretely observed price and return data, for instance, M equidistant observations on each day t, where $t = 1, \ldots, T$. Given a panel of N assets, let $r_{t,i}^{(j)} = p_{t,i}^{(j)} - p_{t,i-1}^{(j)}$ denote the i-th observed intra-day return for the j-th asset on the t-th day, $j = 1 \ldots, N$, and $i = 1 \ldots, M$. We use $r_{t,i}^{(0)}$ to represent the return on the equally weighted market portfolio comprised of all N assets.

A consistent estimator for quadratic variation on the t-th day, $QV_t^{(j)}$, is the realized variance $RV_t^{(j)}$ defined as

$$RV_t^{(j)} = \sum_{i=1}^{M} |r_{t,i}^{(j)}|^2 \xrightarrow{p} QV_t^{(j)}, \quad \text{as } M \to \infty. \tag{3}$$

In the presence of jumps, $RV_t^{(j)}$ in (3) is not a consistent estimator for $IV_t^{(j)}$. Barndorff-Nielsen and Shephard (2004) propose a robust-to-jumps estimator of $IV_t^{(j)}$, known as the realized bipower variation

$$BV_t^{(j)} = \frac{\pi}{2}\left(\frac{M}{M-1}\right) \sum_{i=2}^{M} |r_{t,i}^{(j)}||r_{t,i-1}^{(j)}| \xrightarrow{p} IV_t^{(j)}, \quad \text{as } M \to \infty. \tag{4}$$

The realized bipower variation $BV_t^{(j)}$ is commonly used to construct an estimator of the local volatility $\sigma_t^{(j)}$ due to its robust-to-jumps property.

2.1. Accounting for Intra-day Volatility Pattern

The U-shaped intra-day volatility pattern for asset prices has long been recognized in the high frequency finance literature. Taking into account this type of periodicity has substantial impact on jump detection at the intra-day level. Lahaye et al. (2011) and Boudt and Petitjean (2014) adjust the local volatility measure using the factor proposed by Boudt et al. (2011) and find that this adjustment makes a significant difference in the timing of the detected jumps. Lahaye et al. (2011) argue that this adjustment improves jump detection in the presence of intra-day volatility pattern. Erdemlioglu et al. (2012) also suggest modelling the intra-day periodicity of volatility explicitly in the context of high frequency exchange rate data. There are several parametric and nonparametric approaches in the existing literature. Given the jump diffusion process assumed in equation (1), the ideal volatility adjustment needs to be robust to the existence of jumps.

Bollerslev et al. (2013) utilize an estimate of the Time-of-Day (TOD) volatility pattern based on daily variation measures. At each point i within the day, the relative volatility is measured by the ratio of the form

$$TOD_i^{(j)} = \frac{M \sum_{t=1}^{T} |r_{t,i}^{(j)}|^2 \mathbb{1}_{\{|r_{t,i}^{(j)}| \leq \tau M^{-\varpi}\sqrt{BV_t^{(j)} \wedge RV_t^{(j)}}\}}}{\sum_{t=1}^{T}\sum_{i=1}^{M} |r_{t,i}^{(j)}|^2 \mathbb{1}_{\{|r_{t,i}^{(j)}| \leq \tau M^{-\varpi}\sqrt{BV_t^{(j)} \wedge RV_t^{(j)}}\}}}, \quad i = 1, \ldots, M, \tag{5}$$

where the two constants are $\tau = 3$ and $\varpi = 0.49$. $\mathbb{1}$ denotes the indicator function. The following requirement

$$|r_{t,i}^{(j)}| \leq \tau M^{-\varpi}\sqrt{BV_t^{(j)} \wedge RV_t^{(j)}} \tag{6}$$

effectively guarantees that, asymptotically, only the price movements caused by the continuous Brownian component are retained, and jumps do not enter the volatility adjustment. This truncated measure is first proposed by Mancini (2001). The summation of the squared returns that are due to small price changes provides a consistent estimator of the continuous variation of the Brownian component (see Mancini, 2009). Thus, the TOD volatility pattern constructed using (6) is robust to jumps. Intuitively, setting $\tau = 3$ implies that we classify returns that are larger than three standard deviations measured by the estimated local volatility as jumps. Equation (5) also indicates that we allow the intra-day volatility pattern to be different for different assets $j = 0, 1, \ldots, N$. Bollerslev and Todorov (2011) implement the same approach to take into account the intra-day pattern of volatility.

The implicit assumption that is made when we use this TOD adjustment in (5) is that the volatility pattern is the same throughout the sample period. This may not always be the case. In particular, when we have a long sample period that spans several years, it may not be logical to make such a restrictive assumption. Although in general we expect a U-shaped pattern, certain events such as the global financial crisis (GFC) that affect the economic fundamentals, may cause shifts in the relative magnitudes of the intra-day volatility. Taking into account these factors, we estimate TOD using subsamples to allow for potential structural changes in the volatility pattern, and they indeed display visible differences at different segments of the sample.[2]

2.2. Detection of Intra-day Jumps

We use the test statistics provided by Lee and Mykland (2008) to detect intra-day jumps in the market portfolio and its constituent stocks. There are other jump tests in the literature, for example, the non-parametric test proposed by Barndorff-Nielsen and Shephard (2006) (BNS) and Huang and Tauchen (2005). This widely used BNS test utilizes the discrepancy between QV_t and IV_t to detect the existence of the jump component. However, it can only test for the existence of jumps within a given time interval (usually one trading day). In contrast, the LM test allows us to

[2] We repeat the analysis using the TOD volatility pattern estimated from the entire sample period as a robustness check; there are slightly fewer jumps detected using the univariate jump test. It does not alter the conclusion of our empirical study.

identify the timing of the jumps at the intra-day level. In addition, the LM test is shown to have the best finite performance in Monte Carlo simulations compared with other non-parametric jump tests (see Dumitru and Urga, 2012), whereas the test by Barndorff-Nielsen and Shephard (2006) is known to have severe size distortion in finite samples.

The LM test is very similar to the test proposed by Andersen, Bollerslev and Dobrev (2007). The only difference between these two tests is in their critical values. The test statistic is given by

$$|r_{t,i}^{(j)}|/\hat{\sigma}_{t,i}^{(j)}, \qquad i = 1, \ldots, M, \tag{7}$$

where $r_{t,i}^{(j)}$ is the i-th intra-day return on the t-th day, and $\hat{\sigma}_{t,i}^{(j)}$ is the estimated local volatility, $t = 1, \ldots, T$. Lee and Mykland (2008) suggest using K observations prior to $r_{t,i}^{(j)}$ to estimate $\sigma_{t,i}$, i.e.

$$(\hat{\sigma}_{t,i}^{(j)})^2 = \frac{1}{K-2} \sum_{j=i-K+1}^{i-1} |r_{t,j}^{(j)}||r_{t,j-1}^{(j)}|, \quad \text{and } K = \sqrt{M \times 252}. \tag{8}$$

The estimator in (8) is constructed in a similar way as $BV_t^{(j)}$ in (4), and hence $\hat{\sigma}_{t,i}^{(j)}$ is robust to jumps. Lee and Mykland (2008) use a standard Gumbel distribution and derive the critical value of the following form

$$\frac{\zeta}{c\sqrt{2\ln M}} + \frac{\sqrt{2\ln M}}{c} - \frac{\ln(4\pi) + \ln(\ln M))}{2c\sqrt{2\ln M}}, \tag{9}$$

where $c = \sqrt{2/\pi}$, $\zeta = -\ln(-\ln(1-\alpha))$, and α denotes the daily significance level.[3] On the other hand, Andersen, Bollerslev and Dobrev (2007) suggest using the standard normal distribution to obtain the critical value, which is given by the inverse cumulative density function (cdf) of a standard normal distribution $\Phi_{1-\beta/2}^{-1}$ with $\beta = 1-(1-\alpha)^{1/M}$. We find that the Andersen, Bollerslev

[3]Gilder et al. (2014) point out that there is an error in the original paper by Lee and Mykland (2008) where the constant 4 in the last term is omitted. We decide to use (9) instead of the original critical value given by Lee and Mykland (2008) in this paper.

and Dobrev (2007) critical values are always lower than the ones given by Lee and Mykland (2008), and hence leads to more permissive results on jump detection. Thus we use only the critical value presented in (9), and refer to this test as the LM test throughout the paper.[4]

In order to maintain consistency in the construction of the estimated local volatility and the TOD volatility adjustment, we make the following modification to the TOD adjusted estimate of the local volatility measure in the place of (8) to calculate the LM test statistic:

$$(\hat{\sigma}_{t,i}^{(j)})^2 = \frac{1}{M} (BV_t^{(j)} \wedge RV_t^{(j)}) \times TOD_i^{(j)}. \tag{10}$$

We use the average level of local volatility within each day adjusted by $TOD_i^{(j)}$ in the construction of the LM test statistic (7). We refer to this TOD adjusted version of the LM test as the LM_{TOD} test henceforth.

2.3. Detection of Intra-day Cojumps among Stocks

Although many methods of identifying jumps in individual asset prices have been proposed over the last decade, the detection of concurrent jumps in many assets is still under-explored. Jacod and Todorov (2009) propose a testing framework for the common arrival of jumps in a bivariate process, but the generalization to higher dimensional systems has proven difficult. Given the large panel of stocks considered here, the bivariate cojump test is not ideal. Most literature on cojumps, especially empirical studies (see Dungey, McKenzie and Smith, 2009; Lahaye et al., 2011; Gilder et al., 2014, for example) simply use jump tests on each individual price series, and define cojump as the case when jumps are detected in more than one process at the same time. This approach is commonly referred to as the coexceedance based detection method (Bae et al., 2003). We follow

[4] We conduct the jump test using the critical value given by Andersen, Bollerslev and Dobrev (2007) as a robustness check, the results are qualitatively similar. These results are available upon request.

this strand of literature to conduct both the LM and the LM_{TOD} tests on individual stocks, and count the number of stocks that jump at the same time.

3. Data

We investigate jumps in the US stock market using a dataset constructed by Dungey et al. (2012). The sample period is over nine years from January 2003 to December 2011, which includes the period of the financial crisis associated with the bankruptcy of Lehman Brothers in September 2008 and the subsequent period of turmoil in the US and international financial markets. The effective sample starts from 6 January 2003 and ends on 30 December 2011.[5] The dataset contains 5-minute observations on prices for 500 stocks drawn from the constituent stocks of the S&P500 index during the sample period, obtained from SIRCA Thomson Reuters Tick History. The data cleaning process is fully documented in the web-appendix to Dungey et al. (2012).

The top 100 largest stocks in terms of their market capitalization are used in our analysis as they are highly liquid and hence less prone to market microstructure noise. We then construct an equally weighted portfolio using these 100 stocks as a proxy for the market index. The full list of included stocks can be found in Appendix A.

The intra-day returns and prices start from 9:30 am and end at 4 pm. Observations with time stamps outside this window and overnight returns are removed. Missing 5-minute price observations are filled with the previous observation, resulting in zero inter-interval returns. In the case where the first observations of the day are missing, we use the first non-zero price observation on that day to fill backwards. Approximately 20 price observations which are orders of magnitude away from their neighbouring observations are also removed. The cleaned dataset contains $174,020$ intra-day

[5] The first two days in 2003 are used as pre-sample to estimate local volatility for the LM test, and hence are not included in the effective sample.

5-minute observations on $2,260$ active trading days (77 on each day) for each stock.

The 5-minute sampling frequency is chosen as it is relatively conventional in the high frequency literature, especially for univariate estimation, see, for example, Andersen, Bollerslev and Diebold (2007), Lahaye et al. (2011), and for some sensitivity to alternatives see Dungey, McKenzie and Smith (2009). The volatility signature plots popularized by Andersen et al. (2000) and Hansen and Lunde (2006) also suggest that 5-minute sampling could maintain a good balance between market microstructure noise and estimation bias. Thus the 5-minute frequency is reasonable for the highly liquid stocks considered in this paper.

4. Empirical Analysis

We apply the LM and LM_{TOD} tests described in Section 2 to the equally weighted market index as well as the 100 constituent stocks. In this section we first characterize the features of asset prices in our sample. We then provide the testing outcomes of intra-day jumps, and discuss the effect of adjusting for the intra-day volatility pattern on jump detection.

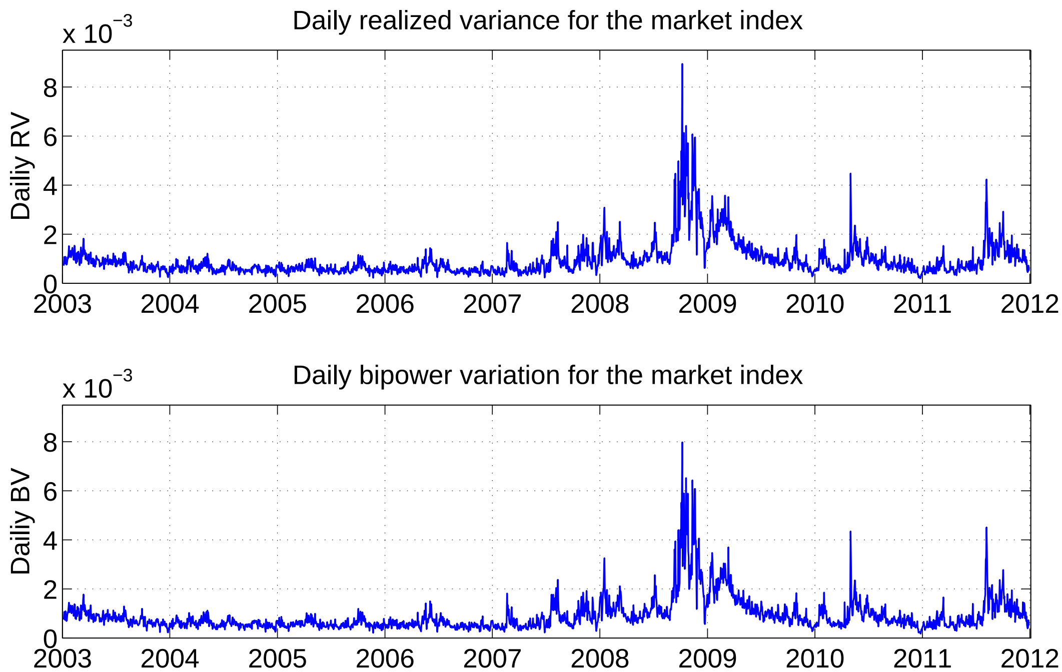
4.1. Changes in Market Volatility

The sample period covers the recent global financial crisis (GFC) which caused drastic changes in the stock market volatility. Thus we first examine the changes in market volatility throughout the entire sample period. Figure 1 plots the daily realized volatility $RV_t^{(0)}$ and realized bipower variation $BV_t^{(0)}$ for the equally weighted market index. The subsample before mid-2007 is much less volatile than the second half of the sample which includes the GFC. Evidently, market volatility has increased considerably since mid-2007, which is usually regarded as the initial emergence of the GFC.[6] Both $RV_t^{(0)}$ and $BV_t^{(0)}$ peak in late 2008 during the few months after the bankruptcy of

[6]The chronology of GFC is a growing literature (see, for example, Anand et al., 2013). Given the timeline by both the European Central Bank and Federal Reserve Bank of St. Louis, financial markets became increasingly vulnerable

Lehman Brothers, the bailout of AIG and the announcement of the TARP (Troubled Asset Relief Program). Two other definite highly volatile periods are mid-2010 during the Greek debt crisis, and late 2011 during the European sovereign debt crisis with the deterioration of economic conditions in the Eurozone as a whole, including Ireland, Portugal, etc. The $RV_t^{(0)}$ and $BV_t^{(0)}$ share a similar pattern in general.

Figure 1: Daily realized variance and bipower variation for the market index



Given the drastic changes in market volatility throughout the sample period supported by Figure 1, we would expect that the intra-day volatility pattern could display quite distinctive features in different segments of the sample. As a result, we estimate TOD separately for each year. We use disjoint annual windows in order to retain enough observations (around 250 trading days) as necessary to produce reliable estimates, consistent with the approach taken by Andersen

since mid-2007.

and Bollerslev (1994). The estimated TOD volatility pattern for each year from 2003 to 2011 is depicted in Figure 2.

The dots in Figure 2 denote the estimated volatility scales at each 5-minute window within the day, and the solid lines are the fitted quadratic curves. The TOD volatility pattern does display a U-shape for each year. As expected, market volatility is usually the highest around opening time and has a peak at 10 am, possibly because this is the time for many scheduled macroeconomic news announcements, and then drops down gradually till mid-day. TOD for 2010 is somewhat different—there is a huge spike at 2:40 pm. We will further explore this phenomenon and discuss possible explanations in the following sections. Several early studies attribute this U-shaped intra-day pattern of volatility (as well as trade volume) to the strategic interaction of traders around market closures (see Andersen and Bollerslev, 1997, and references therein).

4.2. Characterization of Intra-day Jumps

We first present the identified jumps in the market portfolio using the LM and LM_{TOD} tests at 1% significance level in Figure 3.[7] Following the literature, if a jump is detected at time i on the t-th day, we take the size of the market return $r_{t,i}^{(0)}$ as the size of the jump.

The largest jumps during the entire sample period align with the major crisis events in late 2008, early 2009 and early 2010. There are more small-sized jumps in the first half of the sample, while jumps become rarer but larger in magnitude when the market is in distress, consistent with the findings of Novotný et al. (2013). The fact that the stock market has fewer jumps during crisis periods is also observed by Black et al. (2012). In particular, the LM test finds 95 market jumps in 2008 and 104 market jumps in 2011, compared with 120 jumps in 2005. The LM_{TOD} test yields similar results. The adjustment of the volatility pattern has an evident effect on the testing

[7] Test results at different significance levels exhibit qualitatively similar features and hence are not presented here for brevity. These results are available upon request.

Figure 2: TOD intra-day volatility pattern for the market index

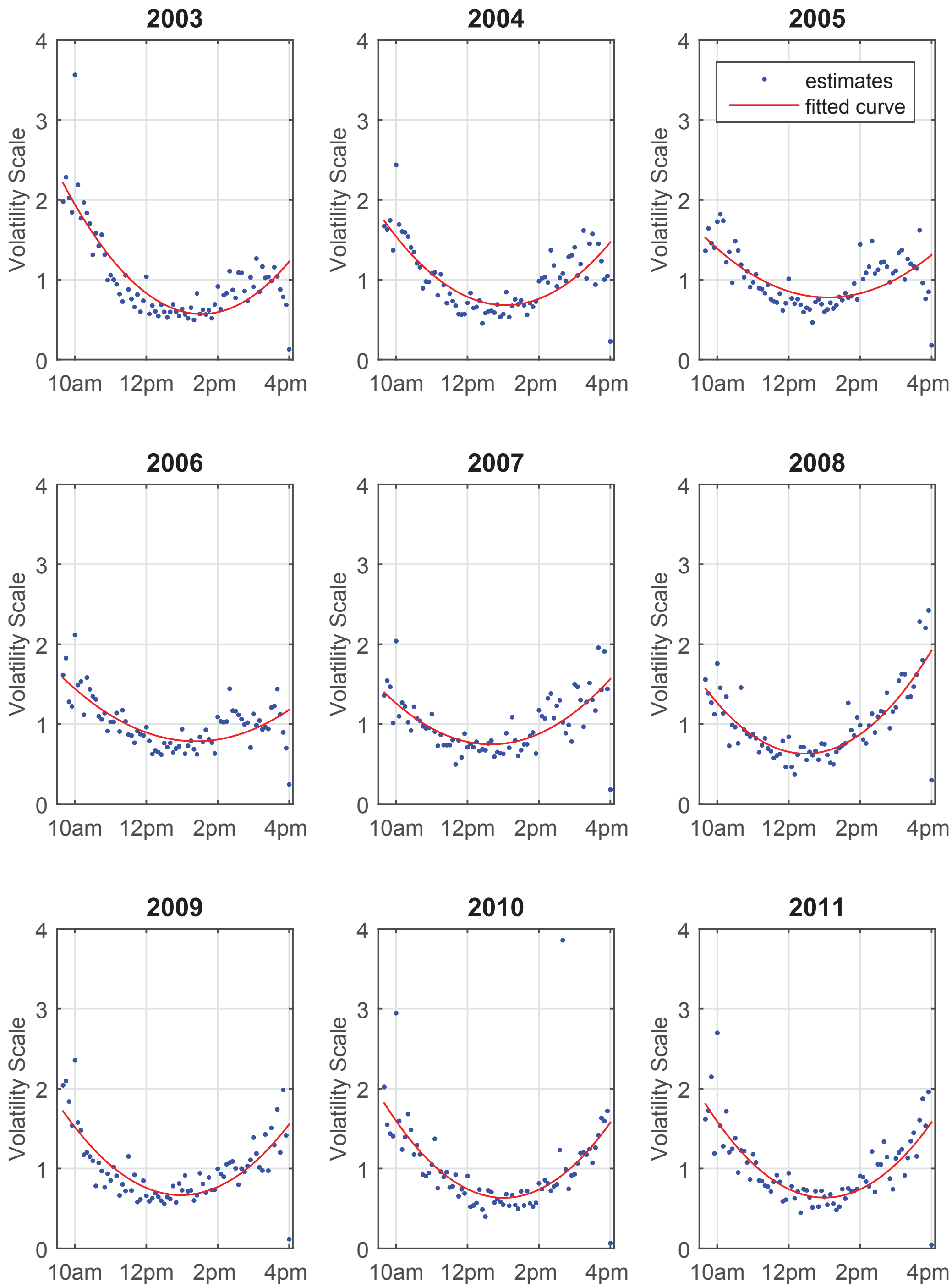
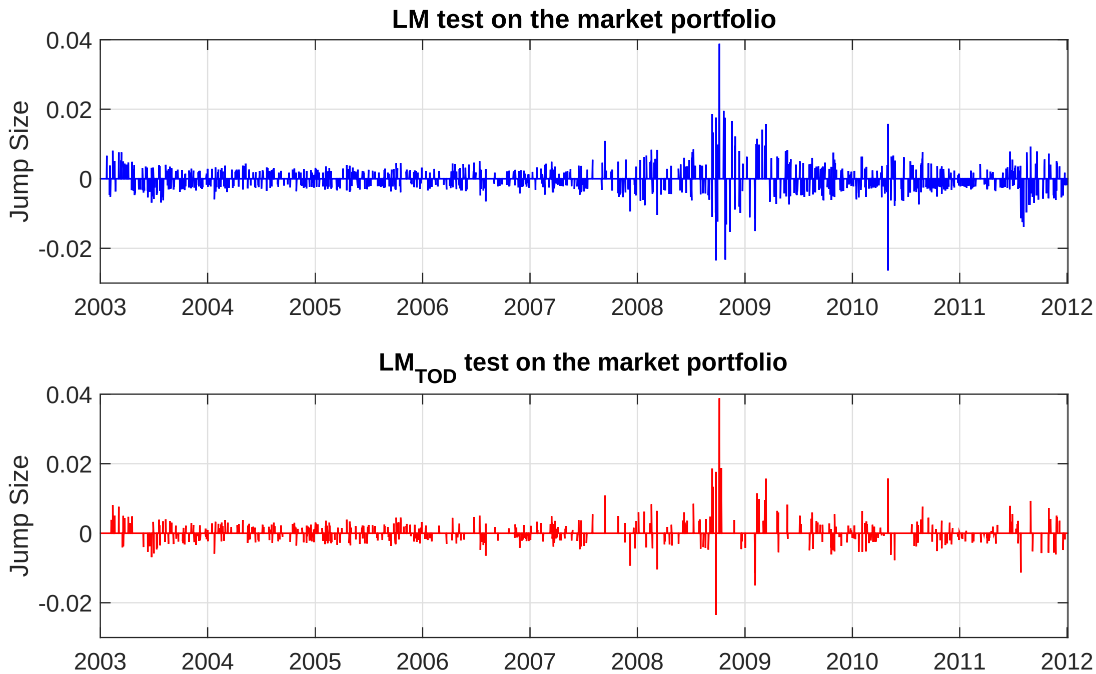


Figure 3: The occurrence and size of jumps in the market index ($\alpha = 1\%$)



outcome. There are fewer jumps detected, and the size of the jump is also smaller in most cases.

One of the most desirable properties of the LM and LM_{TOD} tests is that they are able to pinpoint the timing of the jumps at the 5-minute level. Table 1 shows the number of jumps detected in the equally weighted market index and the underlying stocks at different levels of significance. The results of jump detection in the market index are significantly affected by whether the intra-day volatility pattern is taken into account. For example, at the 1% significance level, the LM test detects 996 jumps in the market portfolio from 684 trading days, while the LM_{TOD} test identifies only 483 jumps from 429 trading days. We also conduct tests on individual stocks and find that, on average across the 100 stocks, there are 1136.8 jumps using the LM test and 422.8 jumps using the LM_{TOD} test. More importantly, using the standard LM test leads to the result that the aggregate market jumps less than individual stocks, supporting the theory that some idiosyncratic jumps are diversified away in the market portfolio. In contrast, after the TOD volatility adjustment, the

Table 1: Number of jumps for the equally weighted market portfolio and its constituent stocks

	Market portfolio		*Individual stocks*	
α	LM	LM_{TOD}	LM	LM_{TOD}
10%	2678	1738	2824.0	1644.4
5%	1957	1153	2110.0	1067.1
1%	996	483	1136.8	422.8
0.1%	423	148	514.9	129.5

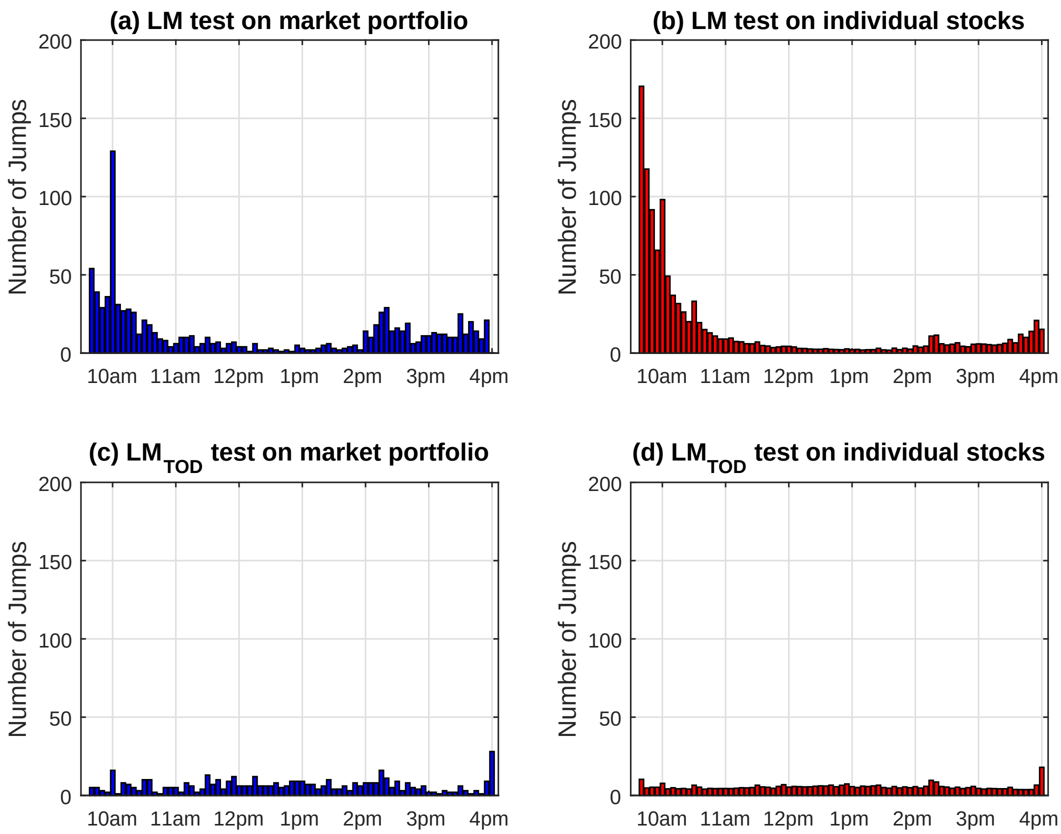
market index always jumps more frequently than individual stocks on average. Both Figure 3 and Table 1 reveal that the decision as to whether to take into account the intra-day volatility pattern has a significant impact on the detection of jumps. For high significance levels 1% and 0.1%, the number of jumps found by the LM_{TOD} test is less than half of the jumps identified by the standard LM test. Given the testing results shown in Table 1, we will base the discussion of subsequent analyses mainly on results obtained using the 1% significance level as the numbers of detected jumps are modest.

As the LM and LM_{TOD} tests are able to pin down the time of the jumps at the 5-minute level, we investigate the distribution of jumps within the trading day. Figure 4 displays the number of jumps detected at each 5-minute observation throughout the trading day for the 2260 days in the sample. Panels (a) depicts the results obtained using the LM test on the market index, and Panel (b) depicts the average number of jumps detected throughout the day for all 100 individual stocks. Most jumps in the market index occur at 10 am, which corresponds to the release of many scheduled macroeconomic news announcements in the US. The majority of the individual stock jumps are in the first 30-minute window after the opening.

Figure 4 shows that the adjustment of the TOD volatility pattern makes a substantial difference in the testing outcome of market index jumps, especially the timing of the jumps. Comparing Panels (a) and (b) of Figure 4 with the intra-day volatility pattern plotted in Figure 2, the distributions of the identified jumps using the LM test share a similar pattern as the intra-day volatility. That

Figure 4: Number of jumps detected at each point of time throughout the day

Intra-day jumps are detected using Lee and Mykland (2008) test with or without adjusting for the TOD volatility pattern. Panels (b) and (d) depict average numbers of jumps across all 100 constituent stocks.



is, the number of jumps is highest at market opening, reaches a peak at 10 am possibly due to the regular release of the macro news announcements, and then displays a U-shape for the rest of the day, with a slight rise shortly after 2 pm, which is roughly the time of the FOMC meeting announcements. However, we do not find the same distributional features with jumps detected using the LM$_{TOD}$ test, as displayed in Panels (c) and (d) of Figure 4. This change resulting from the adjustment of the TOD volatility pattern in the jump test indicates a "trade-off" between jumps and the continuous volatility of the Brownian process. While some jumps are easily detected using the standard LM test, the adjustment of the intra-day volatility pattern effectively teases out these jumps and absorbs their effects into the time-varying volatility. Consequently, a considerable amount of jumps become insignificant using the LM_{TOD} test, and the number of jumps is more evenly distributed throughout the day.

Jumps in a well-diversified index should only be generated by market-level news that induces cojumps across many stocks (Bollerslev et al., 2008). By the same reasoning, cojumps among a large panel of stocks should only be caused by news that has market-wide influence. Comparing Panels (a) and (b) in Figure 4, both the market portfolio and a typical stock tend to have jumps at around 10 am, shortly after 2 pm and close to 4 pm. After adjusting for the intra-day volatility pattern, we still observe such a correspondence between the market index and an average stock in Panels (c) and (d). The distributions of jumps between an average stock and the market portfolio are similar regardless of the adjustment of the U-shaped volatility pattern. Table 2 corroborates the timing of the market index jumps and the cojumps among the constituent stocks at the 5-minute intra-day level and further establishes the association between them. On average more than 15 stocks jump at the times of market index jumps. Incorporating the intra-day volatility pattern in the jump test leads to a lower number of cojumping stocks in almost all cases. Although the adjustment halves the number of market jumps, the majority of the market index jumps still have more than 10 individual stocks jumping at the same time.

Table 2: Characterization of the jump and cojump behavior at 5-min intra-day level

	Market index jump	
	LM	LM_{TOD}
Number of market index jumps	996	483
Mean number of stock jumps	19.7	14.2
Median number of stock jumps	16	10
Percentage(%) of individually tested cojumps		
$n \geq 2$	98.4%	95.0%
$n \geq 5$	91.0%	77.4%
$n \geq 10$	72.5%	50.5%
$n \geq 20$	37.6%	21.7%

Given the fact that the timing of jumps in the market portfolio and cojumps in the constituent stocks coincides with the time of many scheduled macroeconomic news announcements in the US, this type of market-wide new information is likely to be an important factor associated with these jumps. In the next section we investigate the synchronization of market jumps and macroeconomic news announcements.

5. Matching Jumps with Macroeconomic News Announcements

Jumps have been documented as a typical response of financial markets to the changes in economic fundamentals that are revealed by the macroeconomic news.[8] In this section, we study the news announcements during the sample period, and analyze if news can help to explain the role of intra-day volatility adjustment in the jump detection results. Most macroeconomic news announcements in the US are pre-scheduled at a regular frequency. For example, real GDP is announced every quarter, and retail sales and non-farm payrolls are announced every month, all of which are at 8:30 am Eastern Standard Time (EST). Evans (2011) finds that news-related jumps in the US futures markets are larger than non-news-related jumps, and approximately one-third of jumps are related to macroeconomic news, which is in line with the conclusion of Boudt and Petitjean (2014) using the Dow Jones Industrial Average stocks. We extract 13 scheduled macroeconomic news announcements released during the stock market trading hours, which are listed in Table 3. These 13 announcements are released at only five different times points in a day, namely 9:45, 10:00, 14:00, 14:15 and 15:00 EST.

Nine of the announcements are released at 10 am EST every month, and 105 days in the sample have more than one announcement released at the same time. The FOMC meeting announce-

[8]See, for example, Maheu and McCurdy (2004); Simpson and Ramchander (2004); Chatrath et al. (2014); Miao et al. (2013) and references therein.

Table 3: Scheduled release of macroeconomic news items between 9:30 and 16:00 EST

Announcement	Time	Frequency	Start	N.obs
Consumer sentiment	9:45	fortnightly	31-01-2003	213
Business inventories	10:00	monthly	15-01-2003	108
ISM manufacturing index	10:00	monthly	03-02-2003	107
Consumer confidence	10:00	monthly	28-01-2003	109
Factory orders	10:00	monthly	07-01-2003	108
Leading indicators	10:00	monthly	23-01-2003	108
New home sales	10:00	monthly	28-01-2003	108
Unemployment (metro)	10:00	monthly	05-02-2003	106
Unemployment (regional)	10:00	monthly	28-01-2003	108
Investor confidence index[a]	10:00	monthly	09-21-2004	88
Treasury budget	14:00	monthly	22-01-2003	106
FOMC meeting announcement[b]	14:15	6 weeks	29-01-2003	69
Consumer credit	15:00	monthly	08-01-2003	107

[a] The state street investor confidence index was first released in September 2003, but we could only find the exact release dates since September 2004.

[b] We drop the FOMC meeting announcements of federal funds target rate on 22-Jan-2008, 08-Oct-2008, 27-Apr-2011, 22-Jun-2011 and 02-Nov-2011 because they are not released at 14:15.

ment of the federal funds target rate is found to be the most important news by Lahaye et al. (2011) and Gilder et al. (2014). It is usually released at 14:15 EST every six weeks, but we drop five announcements that are released at different times during the sample period as they are not scheduled. Taking into account the fact that some news events occur simultaneously, all of the announcements listed in Table 3 lead to 1335 different news times in total. Table 4 summarizes the matching between identified jumps and news releases at both the daily and intra-day level.

At the daily level, 1183 out of 2260 trading days have at least one announcement released. We allocate the detected jumps in 5-min returns into each daily window and examine the number and percentage of jumps on announcement days and non-announcement days. Without the adjustment of the intra-day volatility pattern, there are more market jumps on announcement days. The probability of observing a market jump on an announcement day is about 6% higher than that on a non-announcement day. News released outside the trading hours is not considered here. Consequently, some news announced at 8:30 in the morning or after market closure on the previous

Table 4: Matching jumps with macroeconomic news announcements

	LM	LM_{TOD}
Daily level[a]		
Number of news days	1183 (out of 2260 days)	
Number of jump days	684	429
jumps|news	390	216
jumps|no news	294	213
$\mathbb{P}$(jump|news)	33.0%	18.3%
$\mathbb{P}$(jump|no news)	27.3%	19.8%
Intra-day (5-min) level		
Number of news times[b]	1335 (out of 11300 observations)	
Number of jumps[c]	219	47
$\text{jump}_{t,i}\|\text{news}_{t,i}$	97	21
$\text{jump}_{t,i}\|\text{no news}_{t,i}$	122	26
$\mathbb{P}(\text{jump}_{t,i}\|\text{news}_{t,i})$	7.3%	1.6%
$\mathbb{P}(\text{jump}_{t,i}\|\text{no news}_{t,i})$	1.2%	0.3%
Number of jumps (lagged responses to news)		
$\text{jump}_{t,i+1}\|\text{news}_{t,i}$	39	9
$\text{jump}_{t,i+2}\|\text{news}_{t,i}$	24	6

[a] The daily level analyses allocate news items and detected jumps on 5-min returns into each daily window and examine the number and percentage of jumps on announcement days and non-announcement days.

[b] The total number of time points considered here is calculated as the product of 2260 trading days and five different time points of news release (9:45, 10:00, 14:00, 14:15, and 15:00). Thus, the number of non-news times used in calculating the conditional probability below is the difference between these two numbers—9965.

[c] Numbers in this row denote the number of jumps occurred at the five time points of news releases across all trading days.

day may induce jumps at the opening time. Situations like this can be falsely classified as observing jumps on a non-announcement day. Therefore, the actual differences in the conditional probabilities may be even higher than those presented in Table 4.[9]

The TOD volatility adjustment once again makes a substantial difference to the conditional probability of observing a jump in the market index. The number of days on which at least one market jump occurs is almost evenly distributed between announcement days and non-announcement

[9]For effects of news released at 8:30 am on financial markets see Dungey, Fakhrutdinova and Goodhart (2009) using equity future market data.

days. This supports the reasoning that the estimated intra-day volatility pattern absorbs some influence of the news announcements. After adjusting for the volatility, news releases do not seem to increase the probability of market jumps, but rather decrease it by 1.5%.

At the intra-day level, we examine only the five time points of news releases across all 2260 trading days to ensure a fair comparison of the conditional probability. This leads to 11,300 5-minute observations. We match the occurrence of jumps and news announcements at these observations to compare the number and percentage of jumps that occurred between the case of news and no news. We allow for the possibility that investors may not react to the news announcements immediately, but rather with a delay. Therefore, when there is a news release at the i-th observation on the t-th day, jumps occurred at the $(i + 1)$ and $(i + 2)$-th observations, that is, jumps within the 10-minute window after the announcement are also considered as results of this announcement.[10] The intra-day level conditional probabilities are shown in the bottom panel of Table 4. They suggest that at the times of macro news announcements, the probability of observing a jump in the market portfolio increases by more than five times than in the case of no news releases using both the standard LM test (from 1.2% to 7.3%) and the LM_{TOD} test (from 0.3% to 1.6%). The last two rows of Table 4 indicate the existence of a lagged response from the market to news releases. There is a considerable number of market index jumps in the 5-minute to 10-minute interval after the macroeconomic news announcements.

We further explore each individual news item and its association with market index jumps. Table 5 presents the number and conditional probability of observing concurrent jumps for all thirteen news announcements examined. Table 5 shows that before the adjustment of the intra-day volatility pattern, the regular release of macroeconomic news announcements is likely to be

[10]We only consider a relatively narrow 10-minute window to obtain a clear cut distinction between different announcements as the release times of a few announcements are only 15 minutes apart.

associated with jumps in the market index. The FOMC meeting announcement, the releases of the consumer confidence and the ISM manufacturing index rank as the top three news items that have the highest probability of concurrent occurrence with market index jumps. More specifically, at the 1% significance level, the FOMC meeting announcement of the federal funds target rate is accompanied by a jump in the market index using the standard LM test within 10 minutes of the announcement on two-thirds of the occurrences. Gilder et al. (2014) similarly conclude that the FOMC meeting announcement has the best match with market index jumps and cojumps across stocks.

A striking feature of Table 5 is that, after the adjustment of the TOD volatility pattern, we observe far fewer jumps in the market index at the time of news releases, except in the case of the FOMC meeting announcements. This observation aligns well with the finding from the previous section that jumps detected after adjusting for the volatility pattern do not occur at the same time within the day as the market index jumps detected using the LM test. More importantly, the effect of the intra-day volatility pattern on jump detection becomes plausible in the context of macroeconomic news announcements. The fact that news about macroeconomic fundamentals has a significant effect on market volatility has been supported by many empirical studies.[11] On the other hand, the strong association between macroeconomic news and asset price jumps has also been well documented. As most of the macroeconomic news announcements are pre-scheduled on a regular basis, their influence on the market may be regarded as part of the intra-day volatility pattern. Once these impacts are controlled for through the volatility adjustment, one can expect that market jumps will not occur concurrently with news releases in most cases.

Given the results shown in Tables 4 and 5, we further hypothesize that after the intra-day volatility pattern has been taken into account, only the news releases which come with a large sur-

[11] For a review of macroeconomic news effects on market volatility, see Rangel (2011).

Table 5: Individual news items — number and conditional probability of jumps[a]

News Item	LM	LM$_{TOD}$	News Item	LM	LM$_{TOD}$
Consumer sentiment (9:45)			*(Un)employment (metro)* (10:00)		
jumps$_{t,i}$—news$_{t,i}$	3	2	jumps$_{t,i}$—news$_{t,i}$	7	1
jumps$_{t,i+1}$—news$_{t,i}$	2	0	jumps$_{t,i+1}$—news$_{t,i}$	1	0
jumps$_{t,i+2}$—news$_{t,i}$	6	1	jumps$_{t,i+2}$—news$_{t,i}$	2	0
$\mathbb{P}$(jump—news)[a]	5.1%	1.4%	$\mathbb{P}$(jump—news)	9.4%	0.9%
Business inventories (10:00)			*(Un)employment (regional)* (10:00)		
jumps$_{t,i}$—news$_{t,i}$	5	1	jumps$_{t,i}$—news$_{t,i}$	5	1
jumps$_{t,i+1}$—news$_{t,i}$	2	0	jumps$_{t,i+1}$—news$_{t,i}$	1	0
jumps$_{t,i+2}$—news$_{t,i}$	2	1	jumps$_{t,i+2}$—news$_{t,i}$	0	0
$\mathbb{P}$(jump—news)	8.3%	1.9%	$\mathbb{P}$(jump—news)	5.6%	0.9%
ISM manufacturing index (10:00)			*Investor confidence index* (10:00)		
jumps$_{t,i}$—news$_{t,i}$	20	5	jumps$_{t,i}$—news$_{t,i}$	12	1
jumps$_{t,i+1}$—news$_{t,i}$	4	0	jumps$_{t,i+1}$—news$_{t,i}$	0	0
jumps$_{t,i+2}$—news$_{t,i}$	1	0	jumps$_{t,i+2}$—news$_{t,i}$	2	1
$\mathbb{P}$(jump—news)	23.4%	4.7%	$\mathbb{P}$(jump—news)	15.9%	2.3%
Consumer confidence (10:00)			*Treasury budget* (14:00)		
jumps$_{t,i}$—news$_{t,i}$	23	1	jumps$_{t,i}$—news$_{t,i}$	3	0
jumps$_{t,i+1}$—news$_{t,i}$	2	0	jumps$_{t,i+1}$—news$_{t,i}$	1	0
jumps$_{t,i+2}$—news$_{t,i}$	1	1	jumps$_{t,i+2}$—news$_{t,i}$	0	0
$\mathbb{P}$(jump—news)	23.9%	1.8%	$\mathbb{P}$(jump—news)	3.8%	0%
Factory orders (10:00)			*FOMC meeting announcement* (14:15)		
jumps$_{t,i}$—news$_{t,i}$	7	0	jumps$_{t,i}$—news$_{t,i}$	16	10
jumps$_{t,i+1}$—news$_{t,i}$	1	0	jumps$_{t,i+1}$—news$_{t,i}$	22	9
jumps$_{t,i+2}$—news$_{t,i}$	0	0	jumps$_{t,i+2}$—news$_{t,i}$	8	2
$\mathbb{P}$(jump—news)	7.4%	1.9%	$\mathbb{P}$(jump—news)	66.7%	30.4%
Leading indicators (10:00)			*Consumer credit* (15:00)		
jumps$_{t,i}$—news$_{t,i}$	4	0	jumps$_{t,i}$—news$_{t,i}$	1	0
jumps$_{t,i+1}$—news$_{t,i}$	1	0	jumps$_{t,i+1}$—news$_{t,i}$	2	0
jumps$_{t,i+2}$—news$_{t,i}$	4	1	jumps$_{t,i+2}$—news$_{t,i}$	0	0
$\mathbb{P}$(jump—news)	8.3%	0.9%	$\mathbb{P}$(jump—news)	2.8%	0%
New home sales (10:00)					
jumps$_{t,i}$—news$_{t,i}$	11	1			
jumps$_{t,i+1}$—news$_{t,i}$	2	0			
jumps$_{t,i+2}$—news$_{t,i}$	1	0			
$\mathbb{P}$(jump—news)	13.0%	0.9%			

[a] For each individual news item, we take into account the possibility that investors may react to the news announcements with a delay. Hence, when there is a news release at the i-th observation on the t-th day, jumps at the i, $(i+1)$ and $(i+2)$-th observations are all counted as results of this announcement (i.e. jumps within the 10-min window since the announcement). The sum of these jumps is used in calculating the conditional probabilities.

prise to market participants cause jumps in the market index. In order to validate this hypothesis, we classify jumps in the market index into three categories: (i) jumps that are detected by both the LM and LM_{TOD} tests; (ii) jumps that are detected by the LM test but not the LM_{TOD} test; (iii) jumps that are detected by the LM_{TOD} test but not the LM test. Thus, according to our hypothesis, jumps in the first category are caused by unexpected news, as the market still reacts to the news after taking into account the intra-day volatility pattern. The second group is caused by news that does not alter investors' perception about economic fundamentals, as the effect of the news can be absorbed into the volatility pattern. The last scenario should be rarely observed. We extract the news contents from the Econoday economic calendar to analyze these events and the resulting market reactions to the announcements.

Table 6 presents the news contents at times that jumps occur in the market index both with or without the adjustment of the volatility pattern. Since some news is quite dated, not all items have an accompanied detailed record as to what happened at the time of the release. We are able to recover 30 out of 34 news releases in this category from the Econoday economic calendar. Results in Table 6 suggest that most of the market jumps detected using both the LM and LM_{TOD} test are accompanied by surprise in the news content (with very few exceptions), which validates our hypothesis. Most jumps in the market index follow the announcements from the FOMC meetings. Although in most cases the FOMC's decision on the federal funds target rate is the same as the market consensus before the announcement, market participants appear to be rather sensitive to the wordings of the FOMC statement. Take the FOMC meeting announcement on 29 June 2006 as an example, the market reflection on that day recorded that although the Federal Reserve raised the target rate by 25 basis points as expected, the FOMC statement noted that the core inflation has been higher in recent months. The FOMC stated that "Some inflation risks remain". Such language is consistent with the view that the FOMC is still seriously considering another rate hike in August but leaves the door open. Stocks showed a notable jump in initial reaction to the FOMC statement. Two jumps detected by the LM_{TOD} test are not found by using the LM test. These jumps fall into the third category and may be due to the error of the statistical procedures.

As Table 6 suggests, almost all of the concurrent jumps detected by both the LM and LM_{TOD} test on the market index come after news that is unexpected by market participants. The deviations from market consensus before the announcement play a vital role in causing immediate market jumps, even after the adjustment of the intra-day volatility pattern. We also investigate the news content on the cases where jumps are detected by the LM but not the LM_{TOD} test.[12] These jumps can be largely attributed to several major scenarios: (i) multiple news with mixed signals are released at the same time, and hence the market does not revise its perception about the overall economic condition; (ii) in addition to the news announcement, there are other macroeconomic events from overseas (such as European crisis, earthquake in Japan, etc.) that impact the financial market; (iii) the market has formed expectations before the time of the news release; (iv) a very small proportion of the jumps are still accompanied by unexpected news. For example, the LM test finds a jump in the market portfolio on 2 February 2004, at the same time as the ISM manufacturing report and the construction spending release, but the LM_{TOD} test does not detect this jump. The market record states that "Stocks ended little changed as a reflection of mixed economic data that includes a strong ISM manufacturing report but soft construction spending and consumer income & spending data". Therefore, in summary, the empirical evidence supports our theory that information contained in macroeconomic news announcements is dissolved into the market through two channels—the volatility of the continuous Brownian component of the price process is elevated by information that does not alter the market's expectation on the economic outlook, but large

[12] There are more than 100 instances of such events, and thus we do not report each individual case due to limited space, but the exhaustive record is available upon request.

Table 6: Cases of intra-day matching between news releases and market jumps identified by both the LM and LM_{TOD} tests

Date	Announcement	Event	Market reaction
$jumps_{t,i}$ — $news_{t,i}$			
13-06-2003	Consumer sentiment	below expectation	unexpected
04-05-2004	FOMC meeting	statement wording	unexpected
28-03-2006	FOMC meeting	statement wording	unexpected
29-06-2006	FOMC meeting	statement wording	unexpected
31-01-2007	FOMC meeting	statement wording	unexpected
14-02-2007	Business inventories	sharp declines	ambiguous
18-09-2007	FOMC meeting	50-basis-point rate cut	unexpected
11-12-2007	FOMC meeting	25-basis-point rate cut	smaller than expected
28-12-2007	New home sales	9% fall	unexpected
30-01-2008	FOMC meeting	50-basis-point rate cut	smaller than expected
14-03-2008	Consumer sentiment	inflation expectation raise	unexpected
23-02-2010	Con./Inv. confidence[a]	drop	unexpected
01-09-2010	ISM index[b]	rise	unexpected
21-09-2010	FOMC meeting	did not announce QE2	disappointed
03-11-2010	FOMC meeting	another $600b purchases	more than expected
01-07-2011	ISM index	rise	better than expected
01-08-2011	ISM index	disappointing	unexpected
01-09-2011	ISM index	mixed	better than expected
$jumps_{t,i+1}$ — $news_{t,i}$			
25-06-2003	FOMC meeting	25-basis-point rate cut	smaller than expected
28-01-2004	FOMC meeting	statement wording	unexpected
22-03-2005	FOMC meeting	statement wording	unexpected
30-06-2005	FOMC meeting	hawkish statement	unexpected
08-08-2006	FOMC meeting	unchanged target rate	expected
21-03-2007	FOMC meeting	statement wording	better than expected
11-12-2007	FOMC meeting	statement wording	unexpected
18-03-2009	FOMC meeting	increase purchase	unexpected
16-12-2009	FOMC meeting	unchanged target rate	expected
$jumps_{t,i+2}$ — $news_{t,i}$			
04-11-2009	FOMC meeting	unchanged target rate	expected
23-02-2010	Con./Inv. confidence	drop	unexpected
03-11-2010	FOMC meeting	another $600b purchases	more than expected

[a] Consumer confidence and the State Street investor confidence index are released at the same time on 23-02-2010.
[b] The ISM manufacturing index is always released at the same time as the construction spending data, but the market reacts mostly to the ISM index, hence we only report the results based on the former.
[c] More detailed market reflections for each of these jumps are available upon request.

price disruptions that reflect rapid re-formation of the underlying expected value of the assets can only be caused by surprising news. Our finding that investors use macroeconomic announcements as a learning mechanism about the economic outlook is consistent with the conclusion drawn by Patton and Verardo (2012) on firm-specific news.

6. Conclusion

Focusing on the largest 100 stocks amongst the constituents of the S&P 500 index, we study the intra-day jumps in both the market portfolio and individual stocks, and consider them as the responses of the stock market to macroeconomic news announcements. The key contribution of this paper is to provide empirical evidence on the following questions: (i) Does the adjustment for the intra-day volatility pattern cause any difference in the jump detection outcomes? (ii) How to use macroeconomic news announcements to explain the difference in jump detection with and without the volatility adjustment?

Firstly, we show that incorporating intra-day volatility patterns in jump detection substantially reduces the number of jumps. This adjustment has lesser impact on the synchronization between market index jumps and concurrent jumps among its constituent stocks. Considering the fact that the Time-of-Day (TOD) volatility may vary over time, we estimate a U-shaped intra-day volatility pattern for each year. The standard LM test identifies more jumps around market opening and closing times than during the trading day, which is a pattern similar to the TOD volatility. The LM test with the TOD adjustment, however, only detects jumps when the effects cannot be absorbed by the time-varying volatility.

Secondly, we find that without the adjustment of the intra-day volatility pattern, there is a strong association between macroeconomic news announcements, in particular, the FOMC meeting announcements, and jumps in the market index. However, most of the macroeconomic news announcements associated with market jumps identified by both the LM and LM_{TOD} tests deliver unexpected news components to market participants. This evidence supports our theory that financial markets respond to macroeconomic news announcements through two channels, namely, the volatility of the continuous Brownian component of the price process and the discontinuous price disruptions. Most effects of the expected news are absorbed into the estimated intra-day volatility pattern, and hence after the TOD adjustment, only unexpected news can cause jumps in the market.

There are several possible directions of future research based on our findings in this paper. Firstly, we use the TOD proposed by Bollerslev et al. (2013) to estimate the intra-day volatility pattern. One could investigate whether other estimation techniques (such as Boudt et al., 2011) yield the same conclusion as to the attribution of jumps and continuous volatility. More importantly, given the link between the intra-day volatility pattern and the regular release of macroeconomic news announcements uncovered in this paper, we should re-examine the empirical results in previous literature, in particular with regards to jump tests with any form of adjustment of the volatility pattern. It all boils down to the research question raised, and the reason for such volatility adjustment in the specific context.

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Appendix A. List of Stocks Included in the Analysis

Table 1: Stocks ordered in terms of the average market capitalization (descending)

1	Exxon Mobil	36	Walt Disney	71	Bank of New York Mellon
2	General Electric	37	3M	72	Lockheed Martin
3	Microsoft	38	Eli Lilly	73	Monsanto
4	Wal-Mart Stores	39	American Express	74	WellPoint
5	Johnson & Johnson	40	McDonalds	75	Gilead Sciences
6	Pfizer	41	Dell	76	Prudential Financial
7	Citigroup	42	Medtronic	77	Baxter International
8	Procter & Gamble	43	Morgan Stanley	78	Sprint Nextel
9	IBM	44	US Bancorp	79	Union Pacific
10	Bank of America	45	Boeing	80	Kimberly-Clark
11	Chevron	46	Unitedhealth	81	Devon Energy
12	AT&T	47	Bristol-Myers	82	DIRECTV
13	JPMorgan Chase	48	Occidental Petroleum	83	Halliburton
14	Cisco Systems	49	UPS	84	Southern Company
15	Intel	50	Comcast	85	Apache
16	Coca-Cola	51	eBay	86	The Allstate
17	Apple	52	Target	87	FedEx
18	Wells Fargo	53	Dupont	88	Corning
19	AIG	54	Lowes	89	Carnival
20	Google	55	Texas Instruments	90	Lehman Brothers
21	Verizon	56	Caterpillar	91	General Dynamics
22	Pepsico	57	Walgreen	92	Illinois Tool Works
23	Oracle	58	Tyco International	93	Costco
24	Altria Group	59	The Dow Chemical	94	Dominion Resources
25	Merck	60	CVS	95	Applied Materials
26	Hewlett-Packard	61	Amazon	96	Automatic Data Processing
27	Conoco Phillips	62	MetLife	97	Ford Motor
28	Abbott Laboratories	63	Kraft Foods	98	Duke Energy
29	Schlumberger	64	Colgate-Palmolive	99	Anadarko Petroleum
30	Amgen	65	Exelon	100	Marathon Oil
31	QUALCOMM	66	EMC		
32	The Home Depot	67	Honeywell		
33	Goldman Sachs	68	News Corp		
34	Times Warner	69	Emerson Electric		
35	United Technologies	70	Yahoo!		

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