Journal of
Risk and Financial Management

Article

Intraday Jumps, Liquidity, and U.S. Macroeconomic News: Evidence from Exchange Traded Funds

Doureige J. Jurdi

Department of Economics and Finance, La Trobe University, Melbourne, VIC 3086, Australia; d.jurdi@latrobe.edu.au

Received: 18 April 2020; Accepted: 3 June 2020; Published: 5 June 2020

Abstract: This paper uses two highly liquid S&P 500 and gold exchange-traded funds (ETFs) to evaluate the impact of liquidity and macroeconomic news surprises on the frequency of observing intraday jumps. It explicitly addresses market microstructure noise-induced biases in realized estimators used in jump detection tests and applies non-parametric intraday jump detection tests. The results show a significant increase in trading costs and elevated levels of information asymmetry before observing jumps. Depth, resiliency, and trading activity are associated with the frequency of observing intraday jumps and cojumps. The ability of liquidity variables to predict intraday jumps persists after controlling for news surprises. Results show that intraday jump realizations affect the price discovery of ETFs.

Keywords: intraday jumps; macroeconomic announcements; liquidity; exchange-traded funds; market microstructure noise; price discovery

1. Introduction

This paper investigates the evolution of realizing jumps in U.S. exchange-traded funds (ETFs) and their implications to the price discovery process. ETFs are attractive financial instruments that offer many benefits to investors. These benefits include exposure to indexes, low trading costs, diversification, tax efficiency, short selling, and limit orders. Besides, the ETF redemption feature facilitates arbitrage so that sophisticated traders can take advantage of and eliminate mispricing (see Ackert and Tian (2000)). The attraction of ETFs has impacted the trading dynamics of market participants due to their role in price discovery. Wallace et al. (2019) show that contribution of the SPY ETF to price discovery has increased significantly from 2% in 2002 to 50% during 2008, to be as important as S&P 500 mini futures. However, these instruments have attracted a significant trading volume from uninformed traders, which has impacted the traded price. Chu and Zhou (2010) find that uninformed traders prefer trading Standard and Poor's Depository Receipts (SPDRs) because these instruments reduce information asymmetry amongst traders, and therefore, uninformed traders reduce their losses to informed traders. Morscheck (2018) shows, using tick-level data for August 2008, a month during the global financial crisis (GFC), that SPDR traded prices significantly deviate from fundamentals due to trader overreaction. Hence, understanding the impact of trading activity on traded prices is important. At the same time, scheduled information plays an essential role in driving ETF prices. Bollerslev et al. (2018) examine how information is processed by financial markets using intraday data for the S&P 500 ETF (SPY) as primary data. The authors estimate the elasticity between abnormal volume induced by news and changes in volatility by regressing jumps in the log-volume intensity on jumps in the log-volatility. Results, based on a sample between 2001 and 2014, show that the sensitivity of abnormal volume changes to those of volatility estimated around the times of macroeconomic news announcements is systematically below unity, especially at times of high economic uncertainty or high dispersion in macroeconomic forecasts. The impact of news on volatility and jumps varies across markets and financial instruments. Sun and Gao (2020) find that macroeconomic news does not play a role in predicting jumps in the Chinese stock index futures markets and show that predictability of jumps is mainly driven by liquidity. Piccotti (2018) identifies jumps and cojumps at the 5-minute frequency using the Andersen et al. (2007) jump detection test for time series of exchange rates dating between January 2007 and December 2010. The authors find that jumps are permanent innovations to investors' information that lead to quote revisions and limit arbitrage.

This paper uses tick-level data to evaluate the impact of macroeconomic news surprises, liquidity, and trading activity on the frequency of observing intraday jumps. The analysis focuses on two important and highly liquid Standard and Poor's Depository Receipts exchange-traded funds (ETFs) tracking the performance of the S&P 500 and gold bullions. Both ETFs rank in the top 50 most liquid ETFs, according to Agrrawal et al. (2014).[1] At the tick level, measures of the second moment are contaminated with market microstructure noise. This noise is mitigated by determining the optimal sampling frequency for each day using robust methods proposed by Bandi and Russell (2006).[2] Intraday jumps are detected using the Andersen et al. (2007) test, which has desirable power and size properties for a variety of jump-diffusion processes. The analysis is extended to investigate liquidity dynamics and macroeconomic news surprise effects around cojumps using a constant sampling frequency. Finally, an assessment of realized jumps contribution to the price discovery processes in ETFs is provided.

The results show that intraday jumps and signed jumps are prevalent in the time series of both ETFs. Shocks to the width and depth dimensions of liquidity drive the occurrence of jumps. Trading activity variables, such as the order flow imbalance and the number of trades, have significant power in predicting the occurrence of jumps. Besides, the results reveal a decline in contemporaneous resiliency at the onset of jumps. Despite the association between some macroeconomic news surprises and jumps, controlling for these surprises does not subsume the contribution of liquidity to observing jumps or signed jumps. Macroeconomic news surprises have an asymmetric impact on signed jumps. Liquidity and macroeconomic announcements cause simultaneous jumps or cojumps across the ETFs investigated. The realizations of intraday jumps have strong implications for price discovery. Post-jump order flow shows that jumps reveal information that affects ETF prices.

The remainder of the paper is organized as follows. Section 2 provides a summary of relevant literature. Section 3 explains the methodology, including non-parametric tests used to identify intraday jumps and the procedure applied to mitigate the impact of market microstructure noise on realized measures. Section 4 describes the data. Section 5 reports the estimation results, and Section 6 concludes.

2. Relevant Literature

Several developments in asset pricing rely on continuous-time diffusion models. In these models, the Brownian motion is a continuous-time process that is Gaussian and symmetric. Discontinuities in the second moment of financial asset returns, often reflecting extreme price reaction to the news, are then accommodated by introducing a compensating jump process to the diffusion model. This results in capturing many salient features of the time series of returns, such as skewness and excess kurtosis. Pan (2002) and Eraker et al. (2003) suggest that including jumps in stochastic volatility models is necessary to account for sudden shifts in volatility. The increasing availability of high-frequency data during the last decade led to significant advances in the quadratic variation theory and its applications in finance. Following the empirical work of Andersen and

---

1 Agrrawal et al. (2014) use a four-factor liquidity scoring algorithm to rank 462 ETFs, based on all four factors. They show that liquid ETFs are characterized by large market capitalization and lower bid–ask spreads. These ETFs attract a large trading volume and have a lower expense ratio.

2 Bandi et al. (2008) evaluate economic implications of the optimal sampling theory to investors. They show that the economic utility of a risk averse investor is improved when relying on variance forecasts constructed using the optimal sampling frequency rather than the 5 or 15-minute forecasts that are commonly used in the literature to mitigate market microstructure noise.

Bollerslev (1998) on intraday volatility measurement using high-frequency data, several non-parametric methods were introduced to estimate realized volatility and disentangle the continuous volatility sample path from the discontinuous component or realized jumps. Barndorff-Nielsen and Shephard (2004) show that the difference between the realized variance and bipower variation estimates the quadratic variation of the discontinued component or jumps. Barndorff-Nielsen and Shephard (2006) develop the asymptotic distribution theory to identify statistically significant jumps. Huang and Tauchen (2005) evaluate alternative jump identification tests using extensive simulations and discuss their finite sample properties. Andersen et al. (2007) find that the decomposition of realized volatility into continuous and realized jump components improves the forecasting accuracy of expected realized volatility. Patton and Sheppard (2015) show that signed jumps have an asymmetric effect on volatility forecasts. Wan et al. (2017) find that positive jumps are more frequent than the negative jumps in the Chinese market. The occurrence of positive jumps is associated with high trading activity and reveals information that impacts subsequent trading activity. Liao (2013) shows that modeling jumps in realized volatility improves tail point forecasts and increases the accuracy of value at risk forecasts for eight individual stocks listed on Chinese stock exchanges.

Identifying the causes of jumps is also important in understanding how asset prices behave. Several empirical studies suggest that macroeconomic announcements cause jumps. Das (2002) and Johannes (2004) use jump-diffusion models and show that unexpected news arrival about the economy is directly related to the occurrence and magnitude of jumps in interest rate markets. Studies based on non-parametric realized volatility and jumps concur with the evidence. Barndorff-Nielsen and Shephard (2006) show that daily jumps in the D.M./dollar rate are associated with macroeconomic announcements. Huang (2018) finds that the number of jumps is higher on macroeconomic announcement days than other days in the U.S. equity and bond markets and shows that different types of news surprises impact the jump hazard rate. Other studies investigate the contemporaneous relationship between macroeconomic news and asset prices. These studies often report elevated levels of intraday volatility around announcement times (Fair 2002; Rosa 2011) and others.

Developments in financial econometrics focusing on jumps have led to identifying the exact timing and size of intraday jumps (Andersen et al. 2007; Lee and Mykland 2008; Jiang et al. 2011), allowing researchers to associate specific macroeconomic announcements with intraday jumps. Evans (2011) shows that macroeconomic announcements cause significant intraday jumps in three U.S. future markets, whose magnitude is significantly larger than other jumps. Lahaye et al. (2011) find that jumps are more frequent on macroeconomic announcement days; however, their magnitude is not consistently different from those occurring on non-announcement days. The magnitude of jumps is largest in U.S. stock index futures markets, followed by U.S. Treasury bonds and currencies. Lahaye et al. (2011) also report that macroeconomic announcements cause cojumps across different asset classes. Dungey et al. (2009) detect a higher number of cojumps in the term structure of the U.S. Treasury market that are associated with scheduled news releases. Jiang et al. (2011) find that return jumps in the U.S. Treasury market are predictable when conditioning on macroeconomic news and liquidity shocks. The authors also show that realized jumps contribute significantly to price discovery in U.S. Treasury securities. Boudt and Petitjean (2014) find that shocks to the width and the number of trades increase the probability of jumps using the constituents of the Dow Jones Industrial Average Index (DJIA).

3. Methodology

3.1. Identifying Intraday Jumps

News arriving at financial markets may result in extreme price movements or jumps that are not captured by a price diffusion process. To compensate for jumps, a logarithmic price p_t is expressed as a jump-diffusion process given by

$$dp_t = \mu_t dt + \sigma_t d\omega_t + \kappa_t dq_t, \qquad 0 \le t \le T, \tag{1}$$

where μ_t is the instantaneous drift with continuous and locally finite variation along the sample path; $\sigma_t > 0$ is the spot volatility component that is assumed to be cádlág; ω_t is a standard Brownian motion; and $\kappa_t dq_t$ denotes the jump component where $dq_t = 1$ if a jump is observed at time t and 0 otherwise. Jumps occur with time-varying intensity λ_t and size κ_t. Andersen et al. (2007) consider whether a randomly selected intraday return realization is subject to a jump. They define intraday returns as

$$r_{t+\xi.\Delta,,\Delta} = \sum_{j=1}^{1/\Delta} r_{t+j.\Delta,\Delta} I(\xi = j), \tag{2}$$

where ξ is an independently drawn uniformly distributed index from the set {1, 2, ..., 1/Δ=M}. The null hypothesis assumes that returns follow a diffusion process; that is, they are normally distributed conditional on instantaneous variance. The alternative hypothesis assumes that returns violate conditional normality causing an intraday jump. According to the jump detection procedure, an intraday return realization is identified as a jump if its absolute value dominates an appropriately scaled realization of bipower variation as

$$\left|r_{t,j}\right| > \Phi_{1-\beta/2}^{-1} \cdot \sqrt{\frac{1}{M} BV_t}, \tag{3}$$

where $\Phi_{1-\beta/2}^{-1}$ is the inverse of the standard normal cumulative distribution evaluated at cumulative probability $(1-\beta/2)$ and $(1-\beta)^M = 1-\alpha$ and α is the daily significance level of the test; $\sqrt{\frac{1}{M} BV_t}$ is the estimate of the instantaneous volatility for each intraday interval $j = 1, .., M$ and BV_t is the bipower variation at day t estimated following Barndorff-Nielsen and Shephard (2004, 2006) as

$$BV_{t+1} = \frac{M}{\mu_1^2 (M\text{-}k\text{-}1)} \sum_{j=k+2}^{M} \left|r_{t,j}\right| \left|r_{t+(j\text{-}k\text{-}1)}\right|, \qquad t = 1, \ldots, T, \tag{4}$$

where $\mu_1 = \sqrt{2/\pi} = E(|Z|)$ is the mean of the absolute value of a standard normally distributed variable, and k denotes a staggered lag. According to Equation (4), when the product of cross return terms is scaled appropriately, the bipower variation consistently estimates the integrated variance. Asymptotically, the bipower variation converges in probability to the integrated variance as

$$BV_t \to \int_0^T \sigma^2(s) ds, \qquad \text{as} \qquad M \to \infty. \tag{5}$$

Multiple intraday jumps κ are identified by

$$\kappa_{t,j} = r_{t,j} \cdot I\left[\left|r_{t,j}\right| > \Phi_{1-\beta/2}^{-1} \sqrt{\frac{1}{M} BV_t}\right]. \tag{6}$$

Andersen et al. (2007) show that Equation (6) has robust power and size properties for alternative specifications of jump-diffusion processes with significant time-variations in volatility when the size of the test $\alpha = 10^{-5}$.

3.2. Mitigating Market Microstructure Noise

According to the quadratic variation theory, the finer the sampling frequency, the more precise the estimate of the integrated variance is. In practice, however, sampling at an ultra-high frequency, such as the tick level, introduces bias to the estimate of the integrated variance due to the presence of market microstructure noise. Bandi and Russell (2006, 2008) identify the optimal sampling frequency based on a bias–variance trade-off between sampling more often and incurring a larger bias, and sampling less often and incurring larger variance in terms of conditional mean-squared error which is given by

$$E\left(\sum_{j=1}^{M} r_{t,j}^2 \text{-} \int_{t\text{-}1}^{t} \sigma_s^2 ds\right)^2 = 2\frac{1}{M} Q_t + o(1)) + M\beta + M^2\alpha + \gamma, \tag{7}$$

where the observed return process is $r^{*} = r^{*} + \varepsilon$. It is decomposed to the efficient price process r^{*}, and the market microstructure noise component ε, which follows a moving average process of order 1. Q measures quarticity, $\alpha = (E(\epsilon^2))^2$, $\beta = 2E(\epsilon^4) - 3((\epsilon^2))^2$, $\gamma = 4E(\epsilon^2)\left(\int_{t-1}^{t} \sigma_s^2 ds\right) - E(\epsilon^4) + 2(E(\epsilon^2))^2$.

Furthermore, Bandi and Russell (2006, 2008) show that the optimal number of observations M^{*} for each day is approximated by

$$\mathrm{M}^{*} \approx \left(\frac{\mathrm{h}\widetilde{\mathrm{Q}}_{\mathrm{t}}}{\widetilde{\alpha}_{\mathrm{t}}}\right)^{1/3}, \tag{8}$$

where $\hat{Q}_t = \frac{\widehat{M}}{3h}\sum_{j=1}^{\widehat{M}} r_j^4$ is an estimate of the integrated quarticity or the strength of the signal based on a relatively large time interval, which renders the measure immune to the noise. The integrated quarticity requires specifying a lower frequency sampling interval. Barndorff-Nielsen and Shephard (2002) suggest using $\widehat{M} = 15$ minute interval, which I adopt. $\tilde{\alpha}_t = \left(\frac{\sum_{j=1}^{M} r_j^2}{M}\right)^2$ is an estimate of the squared second moment of returns or the strength of the noise sampled at the highest observed frequency M during the trading period h.

3.3. Variable Definitions

This section describes the variables used in the empirical analysis. Macroeconomic announcement surprises are calculated following Balduzzi et al. (2001) and Andersen et al. (2003) as

$$S_{j',t}^{i} = \frac{(A_{j',t}^{i} - Med^{i})}{\sigma^{i}},$$

where $A_{j',t}^{i}$ is the realized value of announcement i at time j' during day t; Med^{i} is the survey's median[3] forecast, which is a proxy for its market expected value, and σ^{i} is the standard deviation of the forecast error for the i^{th} announcement in the survey. The numerator of $S_{j',t}^{i}$ translates announcements to surprises, while the denominator standardizes the surprise to facilitate comparison across macroeconomic indicators.

Liquidity variables are constructed at the intraday level after determining the optimal sampling frequency. Liquidity variables cover the depth, width, and resiliency dimensions of liquidity identified in Kyle (1985) and later in Harris (1990). I suppress the time notation in equations unless otherwise stated. Depth at the inner quote is constructed as

$$Depth = \frac{v^{a} + v^{b}}{2},$$

where v^{a} and v^{b} are the volume at best ask and best bid, respectively. Width is measured using the relative quoted spread and the effective spread. The relative quoted spread is defined as

$$RQS = \frac{p^{a} - p^{b}}{mid},$$

where p^{a} and p^{b} are the best bid and ask quotes at the time of the trade, respectively, and $mid = \frac{p^{a}+p^{b}}{2}$ is the bid–ask midpoint price. If the price of market orders is improved to facilitate transactions, then the quoted spread would overestimate transaction costs. In this case, the effective spread is a better measure of actual transaction costs. The effective spread is constructed as

3 Balduzzi et al. (2001) find that the median is an efficient and unbiased predictor of macroeconomic announcement figures.

$$ES = \frac{\left[2D(p - \frac{1}{2}(p^a + p^b))\right]}{\frac{1}{2}(p^a + p^b)},$$

where D is an indicator of the direction of the trade taking a value of +1 and -1 if the trade is identified as buyer initiated or seller initiated, respectively. The direction of trade is identified using the Lee and Ready (1991) algorithm. This algorithm matches trades and quotes by assuming that trades are recorded five seconds following their actual execution time. Ellis et al. (2000) find that the Lee and Ready algorithm correctly classifies approximately 81% of the trade directions on NASDAQ. I use the Lee and Ready (1991) algorithm and compare trades to quotes contemporaneously as recommended by Bessembinder (2003).

Jiang et al. (2011) find that shocks to the depth and width dimensions of liquidity predict the occurrence of jumps in bond prices. I follow the same definition for standardized depth shocks, which are defined as

$$DepthShock_{j-1} = \frac{Depth_{j-1} - \frac{1}{n}\sum_{i=2}^{n+1} Depth_{j-i}}{\hat{\sigma}_{Depth}},$$

where $Depth_{j-1}$ captures the withdrawal of orders before a news event at time j, n is the number of observations used in calculating the mean and standard deviation of depth over intervals $j = 2, .., n$. Standardized shocks to the relative quoted spread are calculated as

$$\mathrm{RQSShock_{j\text{-}1}} = \frac{\mathrm{RQS_{j\text{-}1}} - \frac{1}{\mathrm{n}}\sum_{\mathrm{i=2}}^{\mathrm{n+1}} \mathrm{RQS_{j\text{-}i}}}{\hat{\sigma}_{\mathrm{RQS}}},$$

where RQS_{j-1} captures the relative quoted spread before the news event at time j.

$$\mathrm{ESShock_{j\text{-}1}} = \frac{\mathrm{ES_{j\text{-}1}} - \frac{1}{\mathrm{n}}\sum_{\mathrm{i=2}}^{\mathrm{n+1}} \mathrm{ES_{j\text{-}i}}}{\hat{\sigma}_{\mathrm{RQS}}},$$

where ES_{j-1} captures the relative quoted spread before the news event at time j.

Resiliency captures the price impact of the order flow or the price response associated with one dollar of trading volume at an intraday time interval. The illiquidity ratio proposed by Amihud (2002) is used to measure resiliency; however, it is calculated using relevant trading information obtained from intraday time intervals as

$$resil = \frac{|r|}{DVol},$$

where $|r|$ denotes the absolute value of logarithmic returns calculated using an observed transaction close to open prices during an intraday time interval, and $DVol$ is the accumulated dollar trading volume during an intraday time interval.

Wu and Xu (2000) find that the order flow imbalance is related to price volatility. Jiang et al. (2011) relate the order flow imbalance to the probability of observing jumps. The order flow imbalance is defined as the absolute value of the difference between buying and selling volume as

$$OF\ imbalance = |vol^B - vol^S|.$$

The direction of the trade is obtained by the Lee and Ready algorithm and is used to classify traded volume into buy or sell. Furthermore, the number of trades (NT) contains information about volatility levels (see Jones et al. (1994)) and explains a significant portion of the jumps component of daily realized volatility (see Giot et al. (2010)). The order flow imbalance and the number of trades are scaled by their sample means. In addition, intraday volatility is likely to rise around jump time. It is calculated as the square root of the sum of squared logarithmic returns over three lagged intervals during a trading day.

3.4. Econometric Model

To assess the impact of intraday liquidity and macroeconomic news surprises on intraday jumps, the following probit model is estimated,

$$P(J_t = 1|x) = \int_{-\infty}^{x'\beta} \phi(j)dj = \Phi(x'\beta), \quad (9)$$

where $P(J = 1)$ denotes the probability that a jump occurs, J is an indicator variable equal to one if a jump is realized, and zero otherwise. $\phi(.)$ denotes the standard normal density function, β is a set of parameters that reflect the impact of the regressors in the columns of matrix $\mathbf{x}$ on the probability of observing intraday jumps. The regressors in $\mathbf{x}$ include liquidity and trading activity variables as well as macroeconomic news surprises calculated from survey results. j denotes the intraday time increment. Furthermore, the model is estimated for signed jumps by replacing the left-hand side variable with the probability of positive jumps $P(J^{+} = 1|\mathbf{x})$ and the probability of negative jumps $P(J^{-} = 1|\mathbf{x})$. All models are estimated with robust standard errors. The frequency of observing jumps is estimated at intraday interval j using lagged liquidity, volatility, and trading activity variables in addition to contemporaneous macroeconomic news surprises.

4. Data

This paper identifies intraday jump realizations in the time series of SPDR Spiders and Gold shares. The data is obtained from the Thomson Reuters Tick History (TRTH) database provided by the Securities Industry Research Centre of Asia Pacific (SIRCA). The data covers the period from 1 February 2005 to 30 December 2010 for SPDR Spiders or SPY and 1 July 2007 to 30 December 2010 for SPDR Gold or GLD. The investigation period is convenient for three reasons. First, the period covers the global financial crisis (GFC), where the number and size of jumps are expected to be higher during times of economic uncertainty and financial market turbulence than in normal economic times. In addition, Schlossberg and Swanson (2018) find that jumps occurring during 2008 and 2009 had a significant impact on ETF excess returns. Second, the SPY ETF has become an important source of price discovery (see Wallace et al. (2019)). They have attracted uninformed traded volume, which caused overreaction in traded prices (see Chu and Zhou (2010); Morscheck (2018)), thus making the likelihood of observing jumps higher. Third, traders prefer trading SPY ETFs on days of scheduled macroeconomic news announcements or during the GFC relative to other instruments such as futures (see Wallace et al. (2019)). The record is obtained for all trade and quotes occurring between 8:01 a.m. and 4:00 p.m. on regular trading days or until 1:00 p.m. on days when the exchange closes early.[4]

The macroeconomic announcement dataset consists of a survey of U.S. macroeconomic news releases during the period from January 2005 to December 2010. The dataset is obtained from Action Economics LLC., who acquires macroeconomic forecasts from renowned individual economists and leading institutional economists in the U.S. The dataset contains the date of the release, its time, the actual value of the announced indicator, and the survey statistics for each indicator. There is a total of 26 announcements in the dataset covering a range of indicators about the U.S. economy. Table 1 summarizes the macroeconomic dataset used in the analysis.

Figure 1 plots the optimal sampling frequency in minutes for SPDR Spiders and SPDR Gold. The optimal sampling frequency is estimated using Equation (8). These plots show that the optimal sampling frequency is time varying. This is due to the stochastic nature of the noise to signal ratio. It is high (low) when the signal of the underlying price process is large (small) relative to market microstructure noise. These plots exhibit occasional spikes in the optimal sampling frequency on days when the noise is relatively high, leading to lower sampling frequencies relative to other days in the sample.

[4] Occasionally, data are obtained for timestamps prior to 8:01 a.m. when the optimal sampling frequency is relatively low. This is necessary to match returns with macroeconomic announcements occurring at 8:30 a.m.

Table 1. List of macroeconomic announcements.

Indicator	Freq	Time	μ_s	σ_s	μ_A
Business inventories	M	10:00 *	0.028	1.582	27
Capacity utilization	M	9:15	−0.272	1.989	29
Construction spending	M	10:00	0.290	2.369	25
Consumer confidence	M	10:00	−0.002	3.260	27
Consumer credit	M	15:00	−0.291	3.258	20
Consumer price index (CPI)	M	8:30	−0.106	1.358	30
Durable orders	M	8:30	−0.064	2.341	29
Factory orders	M	10:00	0.300	1.629	22
GDP advance report	Q	8:30	−0.203	1.721	31
GDP second report	Q	8:30	0.201	1.426	31
GDP third report	Q	8:30	−0.660	2.308	30
Housing starts	M	8:30	−0.180	2.703	29
Industrial production	M	9:15	−0.214	2.11	29
Initial jobless claims	W	8:30	0.317	3.916	16
Leading indicators	M	8:30	−0.041	1.157	26
New home sales	M	10:00	−0.265	2.978	30
Personal consumption expenditures	M	8:30	0.062	1.013	29
Personal income	M	8:30	0.192	1.792	29
Producers price index (PPI)	M	8:30	0.278	2.204	30
Private nonfarm payrolls	M	8:30	−0.609	2.201	30
Retail sales (ex-Auto)	M	8:30	0.027	2.385	29
Retail sales	M	8:30	0.006	2.299	29
Treasury budget	M	14:00	0.059	1.538	15
Unemployment rate	M	8:30	−0.156	2.615	28
Institute for Supply Management survey (ISM)	M	10:00	0.241	2.370	28
ISM non-manufacturing	M	10:00	0.070	2.402	27

Notes: The table lists U.S. macroeconomic indicators, the frequency and time (U.S. E.T.) of each announcement per year, the mean and standard deviation of the announcement surprise over the sample period, as well as the average number of forecasts per indicator calculated as the ratio of survey count to the number of announcement releases calculated over the full sample period (January 2005–December 2010). The frequency of the announcements is denoted by Q = quarterly, M = monthly, and W = weekly. [*] Prior to 13 December 2005, the Business Inventories announcements were released at either 8:30 a.m. E.T. or 10:00 a.m. E.T.

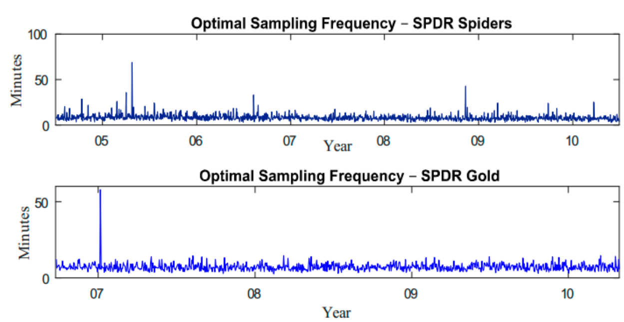

Figure 1. Optimal sampling frequency.

Table 2 reports the descriptive statistics of jumps for each of the ETFs time series in the dataset. The statistics reported in the table indicate asymmetry in jumps frequency. There are more positive jumps in both ETFs than negative jumps. Jumps appeared to be most frequent in 2009; however, the mean and standard deviation of the absolute jump size is most pronounced in 2008 following the arrival of the GFC. The average size and standard deviation of jumps in SPDR Spiders (SPDR Gold) in 2008 are approximately 2.7 times and 3.7 times (1.6 times and 1.4 times) larger than that in 2007, respectively. This is likely due to large swings observed in the prices of ETFs at times of high uncertainty during the crisis. Table 2 also reports the joint distribution of macroeconomic news announcements and jumps. The joint distribution is calculated after matching ETF returns with announcements by fixing announcement times and then sampling around the announcement times at the optimal sampling frequency.[5] The probability of jumps conditional on macroeconomic news announcements reveals that these announcements are more likely to cause jumps in the SPDR Spiders than in SPDR Gold. The likelihood of an announcement to cause a jump over the whole sample period is 5.39% in the SPDR Spiders and 1.11% in SPDR Gold. Additionally, 8.64% (1.48%) of the jumps in SPDR Spider (SPDR Gold) are associated with an announcement of a macroeconomic indicator listed in Table 1. The joint distribution of news and jumps reveals a disproportionate price response between the ETFs investigated. It also indicates that variables other than macroeconomic announcements could be responsible for jumps. This paper focuses on many dimensions of intraday liquidity as potential variables that impact jumps.

Figure 2 plots intraday signed jumps, trading activity, and liquidity variables generated at the optimal sampling frequency. The top panel of the figure shows the time series of SPDR Spiders variables. Signed jumps in the SPDR Spiders series are of a significantly larger size post-2007 and tend to occur more frequently in the second half of the sample period. Large jumps tend to occur during periods of market turmoil and are mainly observed during the GFC and the flash crash of 2010. The quoted spread tends to be decreasing over time; however, it is frequently interrupted by large spikes, which represent higher trading costs. These spikes cluster during the GFC and periods of high uncertainty in the market. The SPDR Spiders, however, exhibited a structural increase in the number of trades and market depth over time. This is likely due to the growth in the ETF industry and the increased use of ETFs as investment and risk management instruments. The figure also shows rising levels in the order flow imbalance post-2007 with occasional spikes in the time series, indicating increasing levels of adverse selection among market participants. In addition, the plot shows improvement in resiliency over time, although the realization of sporadic spikes implies an occasional deterioration in liquidity and recovery time. The bottom panel of Figure 2 plots intraday signed jumps, trading, and liquidity variables for the SPDR Gold series at the optimal sampling frequency. The plot reveals similar behavior to that depicted by the SPDR Spiders time series; however, SPDR Gold experienced a significant decline in transaction costs post-2008. This is likely due to competition between dealers, especially in over the counter (OTC) markets where transaction costs are negotiables between the parties. It is noted that occasional large spikes were removed from the plots to avoid dwarfing displayed dynamics of liquidity and trading activity variables.

Table 2. Descriptive statistics of intraday jumps.

Panel A	**SPDR Spiders (SPY)**						
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**All**
Number of Jumps	29	44	64	65	99	93	394
Number of Positive Jumps	17	28	33	45	49	58	230
Number of Negative Jumps	12	16	31	20	50	35	164
E (jump size ∣ jumps) (%)	0.48	0.41	0.61	1.66	1.1	0.84	0.93
SD (jump size ∣ jump) (%)	0.22	0.12	0.34	1.26	0.63	0.62	0.79
P (jumps ∣ announcements) (%)	3.58	6.8	5.55	4.32	6.63	5.43	5.39
P (news ∣ jumps) (%)	6.48	11.92	8.19	7.47	9.7	7.46	8.64
P (jumps, announcements) (%)	0.05	0.09	0.04	0.04	0.07	0.05	0.06
Panel B	**SPDR Gold (GLD)**						

[5] Occasionally, there are days where the optimal sampling interval exceeds 15 minutes. For these days, the sample is extended to include observations prior to 8:00 a.m. such that 2 observations are always included in the record before announcement times.

	2007	2008	2009	2010	All
Number of Jumps	68	118	130	116	432
Number of Positive Jumps	45	66	76	71	258
Number of Negative Jumps	23	52	54	45	174
E(jump size ǀ jumps) (%)	0.81	1.37	0.93	0.74	0.98
SD (jump size ǀ jump) (%)	0.44	0.62	0.39	0.32	0.52
P (jumps ǀ announcements) (%)	2.45	1.02	0.49	1.01	1.11
P (news ǀ jumps) (%)	3.44	1.33	0.63	0.01	1.48
P (jumps, announcements) (%)	0.02	0.01	0.005	0.01	0.01

Notes: The table reports the number of jumps, number of positive jumps, number of negative jumps, the absolute mean size, and the standard deviation of jumps per year. The joint distribution of macroeconomic news announcements and jumps is calculated using the number of jumps observed at one (two) interval(s) following a macroeconomic announcement for SPDR Spiders (SPDR Gold).

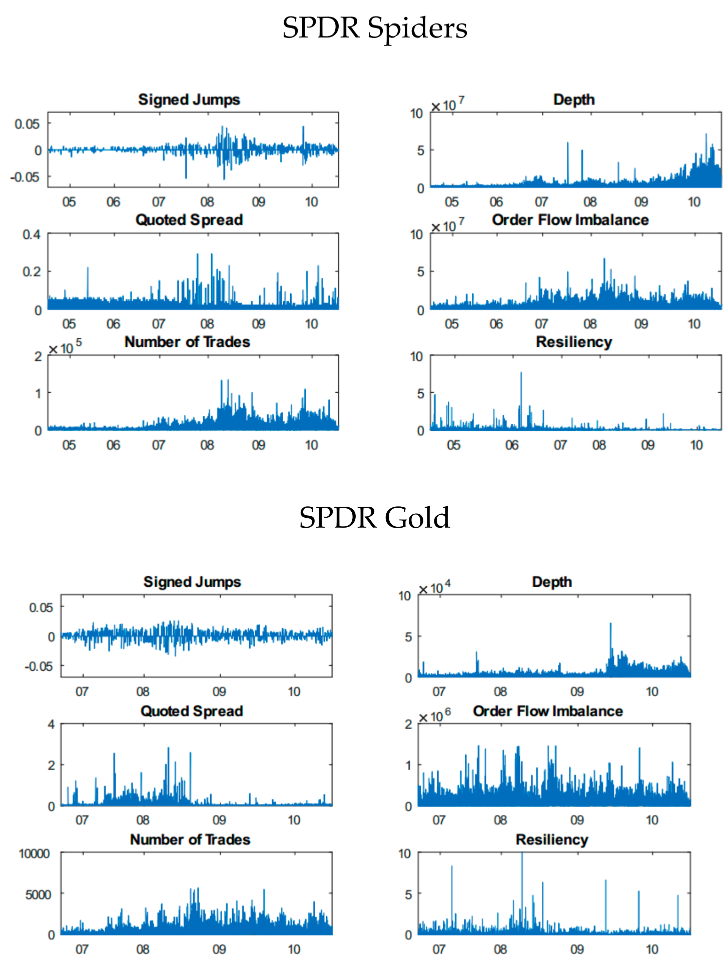

Figure 2. Intraday jumps, liquidity, and trading activity plots.

5. Empirical Results

5.1. Intraday Jumps and Liquidity Dynamics

Table 3 reports the contribution of liquidity and trading activity variables to the probability of observing jumps in SPDR Spiders and SPDR Gold.[6] The results show strong evidence of a surge in

[6] The results in the table are based on sampling all variables at the optimal frequency by starting at 8:01 a.m. on each day.

the costs of executing trades before the occurrence of jumps. Positive shocks to the width dimension of liquidity, in both the relative quoted spread (except in Model 2) and effective spread, reflect a climate of growing uncertainty prior to jumps and signed jumps in both time series. There is ample evidence in theoretical and empirical market microstructure literature that links the width dimension of liquidity to uncertainty. Earlier studies have shown that when uncertainty is high, market makers increase the spread to minimize their losses to informed traders who execute trades based on superior information (see Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Grossman (1992), Seppi (1997), and others).

In terms of depth shocks, the results indicate that market practitioners trading SPDR Spiders withdraw their orders from the market prior to jumps. This is consistent with Copeland and Galai (1983), who show that liquidity suppliers refrain from posting quotes to escape the risk of being picked off by informed traders at times of high uncertainly in the market. Jiang et al. (2011) report a piece of similar evidence using U.S. Treasury bills. In the SPDR Gold series, however, market practitioners continue posting orders around jump times, which improves the ability of the market to absorb large transactions with relatively minimal price impact. The finding is consistent with the findings of Boudt and Petitjean (2014) for the DJIA stocks.

In terms of trading activity, the number of trades drives the occurrence of jumps in the SPDR Spiders series. This suggests that market practitioners minimize the risk of their inventory holdings by closing transactions fast prior to the occurrence of jumps. Earlier studies using low-frequency data find that the number of trades is predictive of jumps (see Chan and Fong (2006); Giot et al. (2010)). At the intraday level, Boudt and Petitjean (2014) find that shocks to the number of trades play a significant role in driving the occurrence of jumps. The number of trades carries a negative sign in the SPDR Gold series; however, the coefficient is not statistically significant.

With respect to resiliency, the results show that liquidity deteriorates at the onset of jumps in both ETFs, giving rise to the possibility of the price impact of trades. This impact depends on how market practitioners resolve newly arrived information. If market practitioners are equally informed, then the price impact of executing trades is immediate. However, if there is asymmetric information among them, then the price impact is gradual, and so is the market recovery. What is certain from the results is that information asymmetry is high prior to jumps. This is shown by the coefficient estimates of the order flow imbalance, which reveal high levels of dispersion in beliefs between market practitioners prior to jumps in both ETFs. As such, informed traders tend to cluster their trades on one side of the market, given their possession of private information about the value of the ETF in anticipation of new information that may unfold with the arrival of jumps. This contradicts the findings of Jiang et al. (2011) and Boudt and Petitjean (2014), who show that the order flow is not informative about jumps in U.S. Treasury markets and the DJIA stocks. However, in an intraday study on ETF arbitrage, Marshall et al. (2013) show that when liquidity declines as a result of widening spreads, the order flow imbalance increases as markets become one-sided in anticipation of arbitrage opportunities due to ETF mispricing. Hence, it is likely that market practitioners speculating on the direction of prices hold onto their strategies until jumps unfold in order to exploit potential gains that may arise from price deviations between the traded price and the net asset values of ETFs.

Finally, the level of volatility is negatively related to the likelihood of detecting jumps. This is likely, since the significance level used in the jump detection test, which helps disentangle jumps from the price process and avoids detecting spurious jumps, is conservative. Boudt and Petitjean (2014) report cases of significant and negative volatility related to the frequency of observing jumps.

5.2. Intraday Jumps, Liquidity, and Macroeconomic Announcement Surprises

Table 4 presents evidence on the relative contribution of liquidity and macroeconomic surprises to the frequency of observing intraday jumps. The evidence is based on estimating probit models, which include liquidity, trading activity variables, and macroeconomic announcement surprises on announcement days. The results show that the predictive power of liquidity and trading activity variables is not subsumed by macroeconomic news surprises. At large, most liquidity and trading activity variables retain their signs and statistical significance, as reported in Table 3. What emerges in Table 4, however, is the significant increase in the number of trades in the SPDR Gold series and their impact on price. Roache and Rossi (2010) show that gold prices are sensitive to scheduled macroeconomic announcements related to economic activity and interest rates and during periods of uncertainty due to the role of gold as a safe-haven asset.

Turning to specific macroeconomic announcement surprises, it is interesting to observe that a negative surprise to consumer confidence and construction spending surveys causes jumps and signed jumps in both ETFs. A positive surprise to the third GDP report causes jumps and signed jumps in the SPDR Spiders ETF. A positive (negative) surprise to the personal income survey (PPI) causes jumps in SPDR Gold. All other statistically significant announcement surprises have an asymmetric impact on signed jumps (second GDP report, personal income in the SPDR Spiders series, and leading indicators, Institute for Supply Management survey (ISM) non-manufacturing, nonfarm payroll, and treasury budget announcement surprises in the SPDR Gold series). It is noted that models in Table 4 are estimated using macroeconomic announcement surprises without including liquidity variables. The effect size and statistical significance of macroeconomic announcement surprises are similar to the ones reported in Table 4, which include liquidity variables. Hence, for brevity, these results are not reported.

5.3. Cojumps Analysis

This section investigates the relationship between macroeconomic news surprises and the probability of observing cojumps across SPDR Spiders and SPDR Gold. Cojumps are statistically significant jumps occurring in more than one time series simultaneously. Cojumps are identified following Lahaye et al. (2011) as

$$cojump_{j,t} = \Pi_i \mathrm{I}(\left|J_{j,t}\right|),$$

where $\mathrm{I}(.)$ is an indicator function that takes a value of 1 when two statistically significant jumps are detected on the two ETF time series simultaneously at the intraday interval j during day t. Because the optimal sampling frequency is time-varying, it is not possible to match the return of the two series for the same timestamp. Instead, a 5-minute frequency is chosen to construct cojumps. This frequency is close to the average optimal sampling frequency of both time series over the sampling period considered. Intraday jumps are detected using the Andersen et al. (2007) test using a significance level of 10^{-5}. Using Equation (10); there are 236 cojumps observed during the overlapping period in the sample from June 2007 to December 2010. About 12.29% of these cojumps occur within the 20-minute interval that follows a macroeconomic announcement. This indicates that simultaneous jumps across SPDR Spiders and SPDR Gold are linked to changes to the fundamentals of the U.S. economy. Table 5 identifies the most important macroeconomic announcement surprises that are linked to cojumps using estimates from a probit model. The model is estimated using all macroeconomic announcements. For brevity, only the statistically significant announcements are reported.

Results in Panel A of Table 5 show that 3 out of 26 macroeconomic announcement surprises (consumer confidence, initial jobless claims, and leading indicators) are statistically significant and cause cojumps in SPDR Spiders and SPDR Gold. Positive surprises to the initial jobless claims and the leading indicators survey result in negative cojumps. A negative surprise to consumer confidence results in cojumps regardless of their sign. Results in Panel B of Table 5 show that liquidity shocks, resiliency, and trading activity are associated with the frequency of observing cojumps in SPDR Spiders and SPDR Gold.

Table 3. Contribution of liquidity and trading activity to the probability of observing jumps.

Model	1		2		3		4		5		6	
Dep. variable	$P(J_{Spiders} = 1\|x)$		$P(J^{+}_{Spiders} = 1\|x)$		$P(J^{-}_{Spiders} = 1\|x)$		$P(J_{Gold} = 1\|x)$		$P(J^{+}_{Gold} = 1\|x)$		$P(J^{-}_{Gold} = 1\|x)$	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Constant	−2.879 ***	0.032	−3.028 ***	0.029	−3.152 ***	0.032	−2.459 ***	0.039	−2.563 ***	0.043	−2.762 ***	0.055
Depth shocks	−0.041 ***	0.015	−0.041 **	0.018	−0.035	0.023	0.053 ***	0.015	0.038 ***	0.018	0.059 ***	0.021
ES shock	0.048 ***	0.016	0.045 ***	0.019	0.039 *	0.023	0.148 ***	0.015	0.126 ***	0.019	0.151 *	0.021
RQS shocks	0.078 ***	0.020	0.036 *	0.021	0.119 ***	0.031	0.073 ***	0.018	0.088 ***	0.021	0.041 *	0.025
NT	0.142 ***	0.011	0.121 **	0.024	0.136 ***	0.013	−0.037 *	0.021	−0.035	0.024	−0.002	0.032
Resiliency	0.640 *	0.359	0.725 *	0.374	−0.022	0.063	−0.233	0.358	0.054	0.081	−0.976 ***	0.34
OF Imbalance	0.038 ***	0.007	0.031 ***	0.009	0.037 ***	0.009	0.077 ***	0.015	0.078 ***	0.019	0.061 ***	0.021
Volatility	−0.028 ***	0.01	−0.020 *	0.011	−0.034 ***	0.010	−0.078 ***	0.025	−0.125 ***	0.03	−0.025 **	0.029
McFadden R^2	7.06		5.19		8.15		3.9		4.08		4.84	

Notes: The table reports the coefficient estimates (Coef) of the probit model and their robust standard errors (S.E.). Models 1–3 report the results for SPDR Spiders. Models 4–6 report the results for SPDR Gold. ***, **, * denote the 1%, 5%, and 10% significance levels, respectively.

Table 4. Impact of macroeconomic news surprises on jumps.

Model	1		2		3		4		5		6	
Dep. Variable	$P(J_{Spiders} = 1\|x)$		$P(J^{+}_{Spiders} = 1\|x)$		$P(J^{-}_{Spiders} = 1\|x)$		$P(J_{Gold} = 1\|x)$		$P(J^{+}_{Gold} = 1\|x)$		$P(J^{-}_{Gold} = 1\|x)$	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	S.E.
Constant	−2.880 ***	0.023	−3.030 ***	0.029	−2.718 ***	0.021	−2.597 ***	0.027	−2.742 ***	0.034	−2.931 ***	0.036
Depth shocks	−0.043 ***	0.015	−0.043 **	0.189	−0.039	0.023	0.027 *	0.014	0.025	0.018	0.024	0.023
ES shock	0.048 ***	0.016	0.045 **	0.199	0.039 *	0.023	0.126 ***	0.014	0.104 ***	0.018	0.132 ***	0.018
RQS shocks	0.079 ***	0.020	0.036 *	0.021	0.119 ***	0.029	0.098 ***	0.016	0.068 ***	0.020	0.122 ***	0.023
NT	0.142 ***	0.011	0.121 ***	0.014	0.137 ***	0.013	0.074 ***	0.014	0.073 ***	0.015	0.064 ***	0.019
Resiliency	0.640 *	0.359	0.725 **	0.370	0.022	0.063	−0.007	0.013	0.001	0.007	0.279 ***	0.003
OF Imbalance	0.038 ***	0.007	0.031 ***	0.009	0.037 ***	0.009	0.036 ***	0.007	0.029 ***	0.009	0.038 ***	0.011
Volatility	−0.287 ***	0.103	−0.206	0.128	−0.349 ***	0.105	−0.791 ***	0.134	−0.864 ***	0.195	−0.578 ***	0.167
Consumer confidence	−0.060 ***	0.014	−0.055 ***	0.013	−0.054 ***	0.013	−0.049 ***	0.014	−0.045	0.013	−0.044 ***	0.012
Construction spending	−0.064 **	0.029	−0.057 **	0.026	−0.060 **	0.027	−0.100 ***	0.038	−0.095 ***	0.035	−0.091 ***	0.034
GDP second report	−0.097 *	0.053			−0.107 **	0.050						
GDP third report	0.066 *	0.037	0.059 *	0.034	0.065 *	0.036						
Initial claims							0.205 **	0.092	0.205 **	0.092		
Leading indicators							−0.177 *	0.100				
Nonfarm payroll							−0.286 **	0.145	−0.332 **	0.147		
Personal income	−0.039 *	0.019			−0.032 *	0.019	0.831 **	0.199	0.640 ***	0.217	1.311 ***	0.172

PPI							−0.872 ***	0.196	−0.686 ***	0.213	−1.335 ***	0.171
Treasury Budget							−0.146 *	0.085	−0.167 *	0.090		
Other announcements	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
McFadden R^2(%)	7.25		5.51		8.17		5.08		4.02		5.79	

Notes: The table reports the coefficient estimates (Coef) of the probit model and their robust standard errors (S.E.). Models 1–3 report the results for SPDR Spiders. Models 4–6 report the results for SPDR Gold. ***, **, * denote the 1%, 5%, and 10% significance levels, respectively.

Table 5. Cojumps, liquidity, and macroeconomic news.

Model	**1**		**2**		**3**	
Panel A						
Dep. variable	$P(cojump = 1\|x)$		$P(cojump^{+} = 1\|x)$		$P(cojump^{-} = 1\|x)$	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**S.E.**
Constant	−2.703 ***	0.02	−2.994 ***	0.03	−3.079 ***	0.034
Consumer Confidence	−0.037 ***	0.011	−0.034 ***	0.01	−0.033 ***	0.01
Initial Jobless Claims	0.107 **	0.055			0.167 **	0.069
Leading Indicators	0.574 *	0.313			0.736 **	0.349
Other announcements	YES	YES	YES	YES	YES	YES
McFadden R^2 (%)	1.00		0.09		4.00	
Panel B						
Dep. variable	$P(cojump=1\|x)$		$P(cojump^{+}=1\|x)$		$P(cojump^{-}=1\|x)$	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**S.E.**
Constant	−3.193 ***	0.167	−3.793 ***	0.266	−3.105 ***	0.184
Depth shocks Spiders	−0.133 ***	0.018	−0.113 ***	0.02	−0.113 ***	0.024
RQS shocks Spiders	0.022 ***	0.005	−0.007	0.023	0.025 ***	0.006
NT Spiders	0.258 ***	0.029	0.192 ***	0.029	0.206 ***	0.058
Resiliency Spiders	−0.031 ***	0.005	−0.040 ***	0.007	−0.036 ***	0.008
OF Imbalance Spiders	0	0.001	−0.0007	<0.0001	0.002	0.001
Volatility Spiders	0.019 ***	0.123	0.075	0.161	0.032	0.03
Depth shocks Gold	−0.493 ***	0.106	−0.687 ***	0.155	−0.229 *	0.013
RQS shocks Gold	0.004 ***	0.001	0.004 ***	0.001	0.003 ***	0.001
NT Gold	−1.138 ***	0.203	−0.647 ***	0.194	−1.336 ***	0.303
Resiliency Gold	0.038 **	0.018	0.026	0.023	0.058 ***	0.04
OF Imbalance Gold	−0.001 **	0	−0.0005	0.001	−0.001 **	0.0005
Volatility Gold	−0.060 *	0.034	−0.032	0.033	−0.107	0.126
McFadden R^2(%)	37.98		37.02		31.67	

Notes: Panel A of the table reports the coefficient estimates (Coef) of a probit model and their robust standard errors (S.E.). The estimated probit models use cojumps and signed cojumps on the left-hand side, as indicated in the column headings above. ***, **, * denote the 1%, 5%, and 10% significance levels, respectively.

Results show consistency in the effect sign of shocks in the depth and width dimensions of liquidity for both ETFs. Before the occurrence of cojumps, there is a decline in the depth and a surge of trading costs in both ETFs; however, trading activity and intraday volatility increase in SPDR Spiders and decline in SPDR Gold. This is likely since traders may use these assets for different motives. While SPDR Spiders may be viewed as an investment or hedging instrument, SPDR Gold is likely to be used, like gold, as a safe haven asset as well (see Baur and Lucey (2010)). Prior to realizing cojumps, resiliency is improved in SPDR Gold; however, it deteriorates in SPDR Spiders.[7]

5.4. Post-Jump Price Discovery

This section investigates whether jumps contribute to price discovery in the ETFs used in this study by estimating the following model,

$$r_{j+1}^{mid} = \alpha + \gamma_{jump} D_{jump} + \beta_1 OF_{j+1} + \beta_2 OF_{j+1} D_{jump} + \epsilon_{j+1} \quad (10)$$

where r_{j+1}^{mid} is the logarithmic rate of return calculated from mid-quote at the end of intraday time interval j, α is the intercept, D_{jump} is a dummy variable that takes a value of 1 if a jump occurs and 0 otherwise, OF the order flow imbalance as defined in Section 3.3, β_1 captures the price impact of the order flow imbalance if no jump occurs, β_2 is the additional price impact of post-jump order flow, ϵ_{j+1} is the error term.

Estimates of Equation (10) are reported in Table 6. Results from Model 1 show that the post-jump order flow contributes to price discovery in the SPDR Spiders time series (β_2 is positive and statistically significant at the 10% level). Although the statistical evidence is weak, the realizations of jumps reveal information that impacts returns. In Model 2, estimates show that the order flow imbalance is negatively associated with SPDR Gold returns (β_1 is statistically significant at the 5% level); however, the effect size is small. Post-jump order flow is positively associated with returns in the SPDR Gold time series (β_2 is statistically significant at the 1% level). The size of the coefficient β_2 is significantly larger than β_1 suggesting that the occurrence of jumps play a significant informational role that affects prices. Results from Models 3 and 4 indicate that the post-jump order flow has a significant and positive effect on the prices in SPDR Spiders and SPDR Gold post the realization of jumps, which indicates that jump realizations contribute to price discovery. Models 5 and 6 reveal a significant informational role associated with post-positive jumps order flow in both ETFs. This role is diminished following the occurrence of a negative jump in the SPDR Gold price time series. Analysis extended to cojumps in Models 7 and 8 confirm the role of regressors shown in Models 5 and 6.

Table 6. Jumps and price discovery.

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Dep. variable	r_{SPY}^{mid}	r_{GLD}^{mid}	r_{SPY}^{mid}	r_{GLD}^{mid}	r_{SPY}^{mid}	r_{GLD}^{mid}	r_{SPY}^{mid}	r_{GLD}^{mid}
$D_{jump,SPY}$	−0.004		−0.0006					
	0.256		0.254					
$D_{jump,GLD}$		−0.007		−0.008				
		0.007		0.008				
$D_{jump,SPY}^{+}$					−0.365			
					0.353			
$D_{jump,SPY}^{-}$					0.377			
					0.371			
$D_{jump,GLD}^{+}$						−0.009		
						0.009		

[7] Estimate of probit models which include macroeconomic news surprises and liquidity variables show similar results to the ones reported in Table 5. Consumer confidence, initial claims, and leading indicators announcements remain significant. News variables do not subsume the information contained in liquidity variables. These results are not reported here for brevity.

$D^{-}_{jump,GLD}$						−0.003		
						0.015		
D_{cojump}							0.009	0.009 **
							0.897	0.897
$OF_{j+1,SPY}$	−0.0001		−1.9E−05	−0.0001	−0.0001		−0.00001	−2.9E−05
	0.0001		0.0001	6.78E−05	0.0001		0.0001	0.0001
$OF_{j+1,GLD}$		−0.0009 **	−0.003	−0.0008		−0.0009 **	−0.003	−0.004
		0.0004	0.003	0.0005		0.0004	0.003	0.003
$OF_{j+1}D_{jump,SPY}$	0.023 *		0.023 *	0.033 ***			0.022 *	
	0.013		0.013	0.011			0.012	
$OF_{j+1}D_{jump,GLD}$		0.307 ***	0.263 **	0.298 ***			0.263 **	
		0.071	0.107	0.089			0.107	
$OF_{j+1}D^{+}_{jump,SPY}$					0.036 **			0.037 ***
					0.014			0.014
$OF_{j+1}D^{-}_{jump,SPY}$					−0.008			0.002
					0.022			0.019
$OF_{j+1}D^{+}_{jump,GLD}$						0.509 ***		0.564 ***
						0.101		0.14
$OF_{j+1}D^{-}_{jump,GLD}$						−2.552 ***		−3.076 **
						0.901		1.31
Constant	0.0012	0.001 ***	0.004	0.001 **	0.001	0.001	0.004	0.005
	0.002	0.001	0.003	0.0007	0.002	0.0006	0.003	0.003
R^2 (%)	0.01	0.3	0.3	3.7	1.8	2.01	0.3	1.8

Notes: The table reports the estimates of Equation (10). The top row for each variable reports the coefficient estimates (Coef), and the bottom row reports the corresponding robust standard errors (S.E.) below. ***, **, * denote the 1%, 5%, and 10% significance levels, respectively.

6. Conclusions

This paper investigates the relative contribution of macroeconomic news and liquidity to the frequency of observing intraday jumps. The optimal sampling frequency is determined to mitigate the market microstructure noise observed at the tick level of a return series. Statistically significant intraday jumps are identified using the Andersen et al. (2007) intraday jump detection test.

The analysis shows that liquidity and trading activity variables are informative about the probability of intraday jumps. The surprise component of scheduled macroeconomic releases induces jumps in SPDR Spiders and SPDR Gold. Results show a decline in posting quotes prior to jumps and an increase in width. There is a heightened level of information asymmetry amongst traders and deteriorating resiliency prior to jumps.

Results identify important macroeconomic announcement surprises that are linked to jumps. The nonfarm payroll (factory orders) announcement surprise is found to be highly significant and impacts the frequency of observing jumps and signed jumps on SPDR Spiders (SPDR Gold). The consumer confidence surprise influences jump and signed jumps in both ETFs. There exists an asymmetric response of jumps to a number of other macroeconomic announcement surprises. Intraday cojumps and signed cojumps are associated with consumer confidence, initial job claims, and leading indicators announcement surprises. Besides, the paper presents evidence that shows a strong association between liquidity and trading activity and intraday cojumps. Lastly, results show that jumps reveal important information to the market, which aids in the process of price discovery for ETFs.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

References

Ackert, Lucy F., and Yisong S. Tian. 2000. Arbitrage and Valuation in the Market for Standard and Poor's Depositary Receipts. *Financial Management* 29: 71–87.

Agrrawal, Pankaj, John M. Clark, Rajat Agarwal, and Jivendra K. Kale. 2014. An Intertemporal Study of ETF Liquidity and Underlying Factor Transition, 2009–2014. *The Journal of Trading* 9: 69–78.

Amihud, Yakov. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5: 31–56.

Andersen, Torben G., and Tim Bollerslev. 1998. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39: 885–905.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega. 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review* 93: 38–62.

Andersen, Torben G., Tim Bollerslev, and Francis X. Diebold. 2007. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics* 89: 701–20.

Andersen, Torben G., Tim Bollerslev, and Dobrislav Dobrev. 2007. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics* 138: 125–80.

Balduzzi, Pierluigi, Edwin J. Elton, and T. Clifton Green. 2001. Economic news and bond prices: Evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis* 36: 523–43.

Bandi, Federico M., and Jeffrey R. Russell. 2006. Separating microstructure noise from volatility. *Journal of Financial Economics* 79: 655–92.

Bandi, Federico M., and Jeffrey R. Russell. 2008. Microstructure noise, realized variance, and optimal sampling. *Review of Economic Studies* 75: 339–69.

Bandi, Federico M., Jeffrey R. Russell, and Yinghua Zhu. 2008. Using High-Frequency Data in Dynamic Portfolio Choice. *Econometric Review* 27: 163–98.

Barndorff-Nielsen, Ole E., and Neil Shephard. 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of Royal Statistical Society Series B* 64: 253–80.

Barndorff-Nielsen, Ole E., and Neil Shephard. 2002. Estimating quadratic variation using realized variance. *Journal of Applied Econometrics* 17: 457–77.

Barndorff-Nielsen, Ole E., and Neil Shephard. 2004. Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics* 2: 1–37.

Barndorff-Nielsen, Ole E., and Neil Shephard. 2006. Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics* 4: 1–30.

Baur, Dirk G., and Brian M. Lucey. 2010. Is Gold a hedge or a safe haven? An analysis of Stocks, Bonds and Gold. *Financial Review* 45: 217–29.

Bessembinder, Hendrik. (2003). Trade execution costs and market quality after decimalization. *Journal of Financial and Quantitative Analysis* 38: 747–77.

Bollerslev, Tim, Jia Li, and Yuan Xue. 2018. Volume, volatility, and public news announcements. *Review of Economic Studies* 85: 2005–41.

Boudt, Kris, and Mikael Petitjean. 2014. Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets* 17: 121–49.

Chan, Choon Chat, and Wai Mun Fong. 2006. Realized volatility and transactions. *Journal of Banking and Finance* 30: 2063–85.

Chu, Quentin C., and Dan Zhou. 2010. Does the "spiders" market attract uninformed trading volume? *Journal of Business & Economics Research* 8: 1–19.

Copeland, Thomas E., and Dan Galai. 1983. Information effects on the bid-ask spread. *Journal of Finance* 38: 1457–69.

Das, Sanjiv R. 2002. The surprise element: Jumps in interest rates. *Journal of Econometrics* 106: 27–65.

Dungey, Mardi, Michael McKenzie, and L. Vanessa Smith. 2009. Empirical evidence on jumps in the term structure of the U.S. Treasury Market. *Journal of Empirical Finance* 16: 430–45.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara. 2000. The accuracy of trade classification rules: Evidence from NASDAQ. *Journal of Financial and Quantitative Analysis* 35: 529–51.

Eraker, Bjørn, Michael Johannes, and Nicholas Polson. 2003. The impact of jumps in volatility and returns. *Journal of Finance* 58: 1269–300.

Evans, Kevin P. 2011. Intraday jumps and U.S. macroeconomic news announcements. *Journal of Banking and Finance* 35: 2511–27.

Fair, Ray C. 2002. Events that shook the market. *Journal of Business* 75: 713–32.

Giot, Pierre, Sébastien Laurent, and Mikael Petitjean. 2010. Trading activity realized volatility and jumps. *Journal of Empirical Finance* 17: 168–75.

Glosten, Lawrence R., and Paul R. Milgrom. 1985. Bid and ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14: 71–100.

Grossman, Sanford J. 1992. The information role of upstairs and downstairs trading. *Journal of Business* 65: 509–28.

Harris, Lawrence. 1990. *Liquidity, Trading Rules, and Electronic Trading Systems*. Salomon Brothers Center Monograph Series in Finance and Economics. New York: New York University.

Huang, Xin, and George Tauchen. 2005. The relative contribution of jumps to total price variation. *Journal of Financial Econometrics* 3: 456–99.

Huang, Xin. 2018. Macroeconomic News Announcements, Systemic Risk, Financial Market Volatility, and Jumps. *Journal of Futures Markets* 38: 513–34.

Jiang, George J., Ingrid Lo, and Adrien Verdelhan. 2011. Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis* 46: 527–51.

Johannes, Michael. 2004. The statistical and economic role of jumps in continuous-time interest rate models. *Journal of Finance* 59: 227–60.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson. 1994. Transactions, volume, and volatility. *Review of Financial Studies* 7: 631–51.

Kyle, Albert S. 1985. Continuous auctions and insider trading. *Econometrica* 53: 1315–36.

Lahaye, Jérôme, Sébastien Laurent, and Christopher J. Neely. 2011. Jumps, cojumps, and macro announcements. *Journal of Applied Econometrics* 26: 893–921.

Lee, Suzanne S., and Per A. Mykland. 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. *Review of Financial Studies* 21: 2535–63.

Lee, Charles MC, and Mark J. Ready. 1991. Inferring trade direction from intraday data. *Journal of Finance* 46: 733–46.

Liao, Yin. 2013. The benefit of modeling jumps in realized volatility for risk prediction: Evidence from Chinese mainland stocks. *Pacific-Basin Finance Journal* 23: 25–48.

Marshall, Ben R., Nhut H. Nguyen, and Nuttawat Visaltanachoti. 2013. ETF arbitrage: Intraday evidence. *Journal of Banking and Finance* 37: 3486–98.

Morscheck, Justin David. 2018. Overreaction in trading: Evidence from the intraday trading of SPDRs during the 2008 financial crisis. *International Journal of Finance & Banking Studies* 7: 21–37.

Pan, Jun. 2002. The jump-risk premia implicit in options: Evidence from an integrated timeseries study. *Journal of Financial Economics* 63: 3–50.

Patton, Andrew J., and Kevin Sheppard. 2015. Good volatility, bad volatility: Signed jumps and the persistence of volatility. *The Review of Economics and Statistics* 97: 683–97.

Piccotti, Louis R. 2018. Jumps, cojumps, and efficiency in the spot foreign exchange market. *Journal of Banking and Finance* 87: 49–67.

Roache, Shaun K., and Marco Rossi. 2010. The effects of economic news on commodity prices. *The Quarterly Review of Economics and Finance* 50: 377–85.

Rosa, Carlo. 2011. The high-frequency response of exchange rates to monetary policy actions and statements. *Journal of Banking and Finance* 35: 478–89.

Schlossberg, Jessica, and Norman R. Swanson. 2018. Jump Spillover and Risk Effects on Excess Returns in the United States during the Great Recession. Available online: http://dx.doi.org/10.2139/ssrn.3208759 (accessed on 1 June 2020).

Seppi, Duane J. 1997. Liquidity provision with limit orders and a strategic specialist. *Review of Financial Studies* 10: 103–50.

Sun, Bianxia, and Yang Gao. 2020. Market liquidity and macro announcement around intraday jumps: Evidence from Chinese stock index futures markets. *Physica A: Statistical Mechanics and its Applications* 541: 123308.

Wallace, Damien G., Petko S. Kalev, and Guanghua Lian. 2019. The evolution of price discovery in us equity and derivatives markets. *J Futures Markets* 39: 1122–36.

Wan, Die, Xianhua Wei, and Xiaoguang Yang. 2017. Liquidity dynamics around intraday price jumps in Chinese stock market. *J Syst Sci Complex* 30, 434–63.

Wu, Chunchi, and Xiaoqing Eleanor Xu. 2000. Return volatility, trading imbalance and the information content of volume. *Review of Quantitative Finance and Accounting* 14: 131–53.