Intraday ETF Trading and the Volatility of the Underlying*

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Abstract

Exchange Traded Funds (ETFs) have drawn concerns from both regulators and academics regarding whether trading in these derivative instruments carries the potential to destabilize underlying cash security markets. This paper contributes to the literature by separating, at an intraday frequency, the impact of informed and noise ETF trading activities on the volatility of the underlying cash market.

Specifically, we study the empirical lead-lag structure between price changes in the SPY (SSGA SPDR S&P 500) ETF and the cash index. Then, we use this measure as an instrument for the density of noise trades in the ETF market, relative to all trades (noise plus informed). We find that ETF noise trades do have an impact, but much weaker than that of informed trades, on the cash index volatility over the following several minutes. Moreover, the power of ETF noise trades in predicting cash index realized volatility decays within a few minutes, while that of informed trades persists.

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1 Introduction

The academic literature has long held conflicting views about the impact of derivative products on the pricing of underlying securities, with some papers pointing out how derivatives can improve the price-discovery process, and others focusing on the potential of trading in derivatives becoming, at times, destabilizing to the price of the underlying cash market.\(^1\) During recent years, this interest has extended to the market for Exchange Traded Funds (ETFs), due to the large volume of trading activity in this sector. For instance, by December 2014, the monthly dollar trading volume of S&P 500 ETFs amounted to one trillion U.S. dollars.\(^2\) This figure amounts to a staggering 38% of the aggregate dollar trading volume for the actual S&P 500 stocks; indeed, secondary market trading in the largest single ETF (SPDR S&P 500: SPY) accounts for as much as 24% of trading in the underlying (see Figure 1). In this paper, we attempt to separately identify “noise trades” and “informed trades,” with the goal of identifying the relationship between noise trades and underlying cash index volatility at an intraday level. We define informed trades as those trades based on private or public information about the valuation of the cash index; noise trades are all other trades (including hedging and speculative trades by both institutional and retail investors).

A recent controversial paper by Ben-David, Franzoni, and Moussawi (2014) finds evidence that a stock with higher ETF ownership—defined as the aggregate proportion of outstanding shares of that stock represented by outstanding shares of all ETFs—has higher intraday volatility. The authors render a plausible reason for their findings that, following the intuition of Greenwood (2005): non-fundamental shocks are propagated from the ETF market to the underlying securities, due to imperfect arbitrage activity between the ETF and the underlying cash index. Ben-David, Franzoni, and Moussawi (2014) focus on the daily-based intraday volatility of stocks (i.e. the mean squared second-by-second return during a trading day). We test this hypothesis using a much more granular time-series

\(^1\)see Danthine (1978), Turnovsky (1983), Stern (1987), and Grossman (1988)

\(^2\)Based on data from the Center for Research in Security Pricing (CRSP); this amount includes ETFs which physically hold S&P 500 index stocks, and not those that hold derivatives as the underlying.
analysis by directly looking into the relationship between intraday ETF trading activities and underlying cash index volatility. It is important to first identify noise trading separately from informed trading, since cash market volatility can be affected by either source of trading. That is, our goal is to separately identify the impact of each on cash markets.

To approach this identification problem, we conjecture that, if informed trading dominates during a particular time period in the ETF market, price discovery will occur more frequently in the ETF (as opposed to the cash market), relative to a period during which noise trading in the ETF dominates. As a consequence, the ETF (derivative) price will lead the underlying cash index price during a period of intense informed trading. Hence, a measure of the strength of the ETF-to-cash-market lead-lag effect is a plausible approximation for the density of informed traders in the ETF market during a particular period of time. We follow a Vector Error Correction Model (VECM) by Hasbrouck (1995) and Hasbrouck (2003) to investigate the lead-lag effect between ETF and the cash index. Specifically, we focus on the S&P 500 cash index (SPX) and the associated State Street Global Advisors’ ETF, SPDR S&P 500 (SPY).

For example, a trader who observes a private macroeconomic signal will take advantage of this information, and may prefer to trade the SPY, instead of trading the underlying cash securities, due to the immediacy and cost efficiency of trading the ETF. Subsequently, arbitrageurs will move the SPX price toward that of the SPY. On the contrary, during days when SPY does not lead SPX, trades of SPY are less likely to be made by informed traders. For instance, traders who observe information related to a particular firm (or, a sector), would trade the stock of that firm (or, a sector ETF, or a basket of stocks in that sector) and the cash index will move first. As a result, while it is impossible to identify whether a single trade is informed or noise, such a lead-lag analysis yields a measure of the density of informed trades during a certain period.

Empirically, based on the results from our VECM model, we find that the lead-lag effect between SPX and SPY varies over time. SPY leads SPX during some trading days, while the opposite sequence is observed on other days. This heterogeneous nature in the lead-lag analysis yields a powerful instrument to differentiate informed ETF trades and
noise ETF trades. Therefore, we can evaluate the impact of ETF trading activities on the cash index during days when noise traders of ETFs are dense, compared with days when informed ones are pervasive.

Next, we examine whether SPY trading activity predicts the volatility of the underlying cash index. Our results suggest that the majority of predictive power of SPY trading can be traced to informed trades. Although we cannot absolutely establish a causal relationship between informed ETF trades and cash index volatility, noise trades indeed lose their predictive power for the volatility of cash index in roughly three minutes.

Other literature related to this puzzle includes Da and Shive (2014), which is consistent with daily return co-movement in the securities in an ETF’s underlying portfolio that is due to arbitrage activities. Alternatively, some authors argue that the existence of ETFs has strong benefits and improves the efficiency of the underlying security prices through the price discovery channel. ETFs accelerate the diffusion of fundamental shocks and improve market efficiency, since they allow informed investors to trade a claim on a basket of assets very quickly at very low cost, compared to trading the actual basket itself. For example, Fremault (1991) develops a model explaining that cross-market arbitrage has a beneficial risk-sharing effect, and serves as a price-correcting mechanism. Supporting this theory, Winne, Gresse, and Platten (2014) find evidence that the introduction of ETFs actually decreases the underlying stock bid-ask spreads. The idea is that ETFs allow a spreading of demand across different inventories.

One similar question, which has been extensively studied, is whether index arbitrage activities between index futures contacts and cash indexes increase the volatility of the cash securities. The evidence in this case is also controversial. Bessembinder and Seguin (1992) find that active trading activity in futures markets is associated with lower volatility in the underlying securities, while unexpectedly high trading volume in futures is positively correlated with the volatility of the underlying. Correspondingly, one may suspect ETFs would only destabilize the cash market in some circumstances. Madhavan (2012) shows that the volatility of underlying securities is exacerbated especially when the cash market

\[ \text{3see Changa, Chengc, and Pinegar (1999) and Roll, Schwartz, and Subrahmanyam (2007)} \]
is fragmented. In a recent paper, [Beneish, Lee, and Nichols (2015)] finds that supply of a given stock is the binding constraint for arbitraging mispricing between futures and cash markets, and demand is much less important. [Ben-David, Franzoni, and Moussawi (2014)] also document more pronounced volatility impact by ETF ownership among stocks associated with lower restrictions to arbitrage (e.g., lower lending fees).

The rest of the paper proceeds as follows. Section 2 introduces ETF arbitrage mechanisms. Section 3 provides the data descriptions. Section 4 summarizes our empirical methodologies and investigates the empirical lead-lag relationship between ETF and the underlying cash index. Section 5 provides the main evidence of the relationship between ETF trading volume and the underlying cash index. Section 6 concludes the paper.

2 ETF Arbitrage

Exchange Traded Funds (ETFs) are derivative securities traded on stock exchanges. Since the introduction of Standard & Poor’s Depository Receipts (SPDR, ticker:SPY) in 1993, ETFs have received a huge amount of public attention and have grown to be one of the most important exchange traded products due to their low trading cost, tax efficiency, and transparency (see Figure 1). At the end of 2010, there were around 130 sponsors offering more than 2,400 ETF products worldwide ([BlackRock (2011)].

ETFs can be viewed as having properties somewhere between those of open-end mutual funds and unit investment trusts. ETF shares can be traded on the exchange during market hours, as well as being created from/redeemed by Authorized Participants at the end of the trading day. A plain-vanilla ETF structure includes the following players: ETF sponsor, Authorized Participants (APs), and investors. In the primary market, APs (e.g., Goldman Sachs) are authorized to surrender or redeem a basket of stocks to the sponsor (e.g., iShares) in exchange for ETF creation units. In the secondary market, APs as well as institutional and retail investors can purchase and sell ETF units on the exchange. Like any derivative product, if there is a price discrepancy between the ETF market price

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4Typically, in 50,000 share or multiples. For a detailed discription, see [Ramaswamy (2011)] available at http://www.bis.org/publ/work343.htm
and its NAV, arbitrageurs can long the cheaper asset, and short the expensive. After
the convergence of prices, they will execute the opposite trade, and profit from the price
difference.

Moreover, the special structure of an ETF allows the AP, which functions like a market
maker, to arbitrage between the ETF market and the underlying market in a different way.
Suppose ETF shares are sold on the exchange at a price lower than the NAV, possibly
a result of excessive selling demand for the ETF from some large institutional investors.
APs can purchase ETF and short the underlying securities simultaneously. At the end of
the trading day, APs can surrender ETF shares to the sponsor in exchange for a basket of
securities to offset their short positions. As a result, APs can secure the profits even if the
market prices of ETF and the basket of underlying securities do not converge at the end
of the trading day. If the ETFs are sold at a premium in the exchange, APs can perform
the reverse operation. This arbitrage channel largely mitigates the AP’s risk associated
with the arbitrage activity because they understand that the profits can be realized at the
end of the trading day.

To further decrease the tracking error, ETF sponsors disseminate
the NAV at a 15-second frequency during the trading day.

Ben-David, Franzoni, and Moussawi (2014) find some evidence that non-fundamental
shocks to the ETF are propagated to the underlying securities. The most related theo-
retical work is Greenwood (2005). Under the framework of Greenwood (2005), the non-
fundamental shock is transmitted by risk-averse arbitrageurs. In order to provide liquidity
with an exogenous positive demand on the ETF, arbitrageurs have to short the ETF at
an increased price to compensate them for the risk. In the meantime, they have to hedge
the short position by longing the underlying basket. In order to compensate for this long
leg, the underlying price will go up. Eventually, since the fundamental value remains the
same, both the prices of ETF and underlying securities will reverse.

Of course, this depends on the ability of the sponsor to take and deliver the required positions.
Second-by-second trades and quotes data for S&P 500 futures (E-mini S&P 500 Futures: ES), S&P 500 ETF (SPDR S&P 500 ETF: SPY) and S&P 500 cash index (SPX) are obtained from Bloomberg Professional Service. For E-minis, we use the shortest time to expiry contract and switch to the second shortest contract one day before expiration. For example, we use ESH15 till Mar 19, 2015 and switch to ESM15 on Mar 20, 2015. ESH15 is the 2015 March contract expiring on Mar 20 and ESM15 is the 2015 June contract. Due to the limited historical data available on Bloomberg, our sample starts on Mar 04, 2015 and ends on Sep 17, 2015, totaling 137 trading days.\footnote{We exclude Jun 19, 2015 which is a trading day. Bloomberg obtains S&P 500 index data from Standard & Poor’s. Bloomberg confirms that S&P failed to provide a second-by-second consecutive SPX series on that day.} We only consider data during market hours between 9:30:00 and 16:00:00 Eastern Time (EDT or EST). When there are multiple bid/ask prices within one second, the first available price is considered. We use the mid-point of the best bid/ask quotes to compute one second log returns for SPX. To measure the volatility of the cash index, we compute the uncentered mean of square of one-second SPX returns.

In Panel A of Table 1, we report the summary statistics for intraday SPY trading activities. We compute the average per second SPY share trading volume during a 600-second window\footnote{Since SPY trades do not occur every second, the purpose of this 600-second aggregation is to avoid zero trading volume where logarithm is not defined. Also, the choice of 600 seconds coincide with the first set of main results.} and take the logarithm of this quantity $volume_t$. We first report the mean and standard deviation of $volume_t$ by pooling all trading days. To measure the variation of trading activities within a trading day, we also compute the daily standard deviation of $volume_t$ and report the mean of these daily standard deviations. The average variation of $volume_t$ within a trading day is 0.58 (or $e^{0.58} \approx 78\%$), while the pooling variation is 0.70 (101\%). Panel B of Table 1 reports the summary statistics for the variation of one-second returns for ES, SPX, and SPY. Within each trading day, we compute the variance of one-second returns. Then, we report mean, standard deviation, minimum, quartiles, and maximum of the intraday variance over the sample of 137 trading days. E-minis have
the highest intraday variance, while the index, SPX, has the smallest. This indicates that significant noise trading occurs in ES and SPY, relative to SPX. Also, note that the distributions of variances are right-skewed.

Table 2 examines the staleness of the price series. We compute the autocorrelation and cross-correlation of one-second returns for ES, SPX, and SPY within each trading day. Reported are the mean and standard deviation of these statistics (in percent) across all sample days. When \( s = 0 \), reported is the contemporaneous correlation among the three series. The average correlation between ES and SPY, and between SPX and SPY, are approximately 0.67, higher than the average correlation between ES and SPX, which is 0.55. Although most correlation coefficients are small in terms of absolute value, correlations with lagged returns yield some interesting insights. In Panel A of Table 2 the E-mini return is negatively correlated with its one-second lagged return, while both SPX and SPY returns are not correlated with lagged ES returns. Panel B shows that all the three series are positively correlated with lagged SPX returns, up to ten seconds \( (s = 10) \). In Panel C, ES and SPX returns are positively correlated with lagged one-second SPY return. The analysis of autocorrelation indicates the possible lead-lag directions that we will explore in a structural model in the next section.

4 Lead-Lag Effect between Futures, ETF, and Index

4.1 Methodology

The main hypothesis that we test is whether ETF trading volume by so-called "noise traders" impacts the volatility of cash markets more so than if the ETF did not exist. We name this the Excess Volatility Hypothesis (EVH). The EVH will be true if the existence

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8 For ES and SPY, we choose the first available best bid and best ask price within a second. Data from Bloomberg provide the time stamp only with a second level precision. Within one second, there are multiple records of best bid and best ask prices for ES and SPY, while only one price for SPX. It remains a question whether the SPX quote price which Bloomberg provides is computed at the beginning, or the end, of each second. Given the fact that, based on our choice of ES and SPY, the contemporaneous correlation of one-second return is much higher than the cross-correlation of lagged returns, SPX price from Bloomberg is believed to be computed at the beginning of each second.
of ETFs facilitates trading on noise that is less pronounced in pure cash index markets without an ETF.

A serious econometric problem in testing the EVH is to separately identify noise trades and informed trades. Informed ETF trading activities impact cash index through a price discovery channel which mainly improves the market efficiency, while noise trades of an ETF introduce non-fundamental supply and demand shocks which are likely to be propagated to the cash market. We approach this identification problem by analyzing the lead-lag relationship between futures, ETF, and cash index. Presumably, more informed trading occurs in one market if the price series in this market leads the other two. Futures contracts are included in order to address the concern of another potential market where price discovery occurs. As shown in Figure 2, the notional amount of S&P 500 E-mini trading volume\(^9\) is equivalent to dollar volume in the overall S&P 500 cash market.

We follow the VECM approach in Hasbrouck (1995) and Hasbrouck (2003). Hasbrouck (2003) investigates the price discovery channel among floor-traded index futures contracts, ETFs, and electronically traded small denomination futures contracts (E-minis). He provides evidence that price discovery in E-minis lead the other two. In the rest of this subsection, we provide a brief description of the Hasbrouck (2003) model. We consider a time series of vectors \(\{p_t\}_{t=0}^T\) consisting of \(N\) elements \(p_t = [p_1^t, \ldots, p_n^t, \ldots, p_N^t]'\), where \(p_n^t\) is the \(n\)-th logged price at time \(t\). The process \(\{p_t\}_{t=0}^T\) is cointegrated provided that each of its element is integrated of order one, and that there is a linear combination(s) of them such that \(p_t'\beta\) is stationary, where \(\beta\) is a \(N\)-by-\(M\) matrix, and \(M\) is the total number of linearly independent cointegrating vectors. In the case of a price triplet which includes E-mini futures, ETF, and cash index, the number of linearly independent cointegrating vectors is two. The cointegration property stems from the nature of the futures and ETFs, which are essentially claims on the same index, so that the price differences between any two of them will not diverge. Note that \(p_t'\beta\) may not necessarily be a zero-mean process since the ETF holds a cash component from the dividend yield, which is absent in the

\(^9\)Daily futures data are obtained from Wiki Continuous Futures on Quandl.com. We only consider continuous \(\#1\) futures, defined as the shortest time to expiry contracts.
price of the underlying index. Hasbrouck (2003) points out that this cash component is not likely to change within a single trading day, since dividends are paid out at the end of the day prior to the ex-dividend day. Therefore, for each trading day, an error correction term needs to be added into a classic VAR model, and our VECM model reads as:

\[ \Delta p_t = \gamma (Fp_{t-1} - \mu_z) + A_1 \Delta p_{t-1} + A_2 \Delta p_{t-2} + \cdots + A_M \Delta p_{t-M} + u_t, \]

where \( \Delta p_t \) is the first order difference of the price vector: \( p_t - p_{t-1} \), matrices \( A_1, \ldots, A_M \) are the coefficients in front of the autoregressive terms, \( u_t \) is the innovation term, and \( \gamma (Fp_{t-1} - \mu_z) \) is the error correction term. Since the cointegration property can be easily identified as the price differences between any two of them is stationary, we let:

\[ F = [\iota_{N-1,1} - I_{N-1}], \]

where \( \iota_{N-1,1} \) is a \([N-1]\)-by-1 vector whose elements are identically equal to one and \( I_{N-1} \) is a \([N-1]\)-by-\([N-1]\) identity matrix. Following Hasbrouck (2003), we constrain a set of coefficients to lie on a function of Polynomial Distributed Lags (PDLs), in order to reduce the number of coefficients. That is:

\[ A_i = C_0 + C_1 i + C_2 i^2 \cdots + C_d i^d. \]

We include up to 300-second lags in the VECM estimation and apply second-degree PDLs (\(d=2\)) over 1-10, 11-20, and 21-30 seconds and zero-degree PDLs (\(d=0\)) over 31-60, 61-120 and 121-300 seconds.

The VECM is estimated in two steps. In the first step, we estimate \( \hat{\mu}_z \) as the daily average second-by-second price differences, i.e., the long-run expectation of \( Fp_{t-1} \). In the second step, estimates of \( \hat{A}_s \) and \( \hat{\gamma} \) are obtained by ordinary least squares (OLS). Then, we compute the impulse response functions. The idea is to consider the price response \( \Delta p^*_s \), for \( s \geq t \), given a unit shock from the \( n \)-th price in the presence of no other shocks, i.e. \( u_t = e_n \), where \( e_n \) is a \( N \)-by-1 vector with the \( n \)-th element equal to one and the rest

10http://pages.stern.nyu.edu/~jhasbrou/
equal to zero. Also, we assume no other shocks in the past or the future:

\[ u_{-\infty} = \cdots = u_{t-1} = u_{t+1} = \cdots = u_{\infty} = 0, \]

\[ Fp_{t-1} - \mu_z = 0. \]

Therefore, \( \Delta p^n \) can be recursively computed and the long-run price response function is the summation: \( \Delta p^n = \sum_{t}^{\infty} \Delta p_s \). In practice, we compute the price impact within a 600-second window.

\[ 4.2 \quad \text{Empirical Lead-Lag Relationship} \]

We summarize the empirical results of long-run response functions in Table 3 and Figure 3. Firstly, we study the lead-lag relationship only between ES and SPY. A daily VECM is performed including only two series, ES and SPY, and we compute the resulted impulse response functions. Panel A of Table 3 summarizes the distribution of the impulse response functions for our sample of 137 trading days. Our evidence contradicts the results in Hasbrouck (2003) who concludes that E-minis lead SPY. We find that, during most of the trading days in our sample, the long-run response function given a shock from SPY (\( \Delta p^{SPY} \)) is much stronger. The 25-th percentile of \( \Delta p^{SPY} \) is 0.69, while the 75-th percentile of \( \Delta p^{ES} \) is only 0.30. This evidence suggests that information often reaches the ETF market faster than the futures market. This lead-lag relationship is puzzling, given that the trading volume of E-mini futures dominates that of SPY, as shown in Figure 2 which suggests that E-minis market has more liquidity and is the venue of choice for traders. In addition, the consensus perception of both academics and practitioners is that ES market is the center for price discovery (see Budish, Cramton, and Shim (2015)).

On the contrary, our findings coincide with another commonly accepted hypothesis that price discovery is more likely to occur in places with lower trading costs. Trading cost in terms of tick size is much smaller in the SPY market than in the ES market. Currently, the tick size for SPY is one penny of a share. It is equivalent to 0.10 index point since the price of ETF is about one-tenth of the index level. Meanwhile, the tick
size for E-minis is 0.25 index point. In addition, there is evidence indicating that price discovery started to occur in the SPY market since the launch of decimal pricing by the NYSE and AMEX on Jan 29, 2001. Chou and Chung (2006) find that the information share (a measure of fraction of the common martingale component conveyed by each cointegrated series) of SPY increases during Feb to Apr 2001, though E-minis still play a dominant role in price discovery. Further, Tse, Bandyopadhyay, and Shen (2006) find that the information share of SPY (traded on ArcaEx) becomes greater than the information share of E-minis based on data from May to July 2004. Wallace, Kalev, and Lian (2015) compute the information share following Hasbrouck (1995) using data from 2002 through 2013. Their evidence suggests a strong leading effect from E-minis before 2004 and the lead-lag relationship starting to reverse in 2008. At the end of 2013, SPY yields an information share of 70%, while the information share of E-minis falls to 30%. Due to the high correlation of one-second return of SPY and ES in our sample of 2015, it is impossible to obtain a meaningful number of information share, but our point estimates of long-run response function yield consistent conclusion with the aforementioned literature.

Next, we turn to analyze the lead-lag effect between SPX and SPY. As shown in Panel B of Table 3, the evidence is not conclusive. We do not observe a homogeneous lead-lag relationship, while both $\Delta p_{SPX}$ and $\Delta p_{SPY}$ have similar means but large variations. It suggests that SPY leads SPX during about half of the total trading days, while SPX leads SPY during the rest. A joint analysis of the lead-lag effect among ES, SPX and SPY is performed by running VECM with the three price series. Results are reported in Panel C of Table 3 and Figure 3. The results in Figure 3 coincide with previous pairwise analyses. $\Delta p_{ES}$ is consistently swinging around zero, while $\Delta p_{SPX}$ and $\Delta p_{SPY}$ are competing over time. This heterogeneous nature of the lead-lag effect between SPX and SPY indicates that the proportion of informed traders over noise ones in the SPY market are not constant. We conjecture that SPY trading activities on days when SPY

\footnote{The essence in computing information share is to twist the covariance matrix of the residual vector from the VECM. People conduct Cholesky decomposition on the covariance matrix (permute all the possible orders of the residual vector) to obtain a lower bound and an upper bound of the information share. In 2015, the one-second return correlation coefficient between ES and SPY is around 0.7 so that the gap between the lower bound and upper bound is substantial.}
leads SPX are more likely to be conducted by informed traders. For example, a trader who observes a private macroeconomic signal will take advantage of this piece of information and she prefers to trade SPY, instead of trading the cash index due to immediacy and cost efficiency. Then, arbitrageurs will move the cash index price towards SPY. On the contrary, during days when the cash index leads SPY, trades of SPY are less likely to be executed by informed traders, since price shocks caused by SPY price changes are more likely to revert. This lead-lag relationship yields an identification strategy to separate the whole sample of trades into two groups of days, with one group containing more informed trades than the other. Therefore, we are able to study if there are any heterogeneous impact from SPY trades on the underlying cash index volatility between these two groups.

5 Empirical Evidence on Cash Index Volatility

5.1 Contemporaneous Evidence

Based on the long-run price response function, $\Delta p^{SPX}$ and $\Delta p^{SPY}$, we classify trading days into two groups, one group consisting of days when SPY leads SPX (i.e. $\Delta p^{SPY} \geq \Delta p^{SPX}$), and the other group consisting of days when the cash index leads SPY (i.e. $\Delta p^{SPX} > \Delta p^{SPY}$). A dummy variable, $I_{ETF}$, is constructed equal to one during days when the ETF leads the cash index, and zero, otherwise.

We define that SPY leads SPX in the context that, given a one unit shock from SPY, the long-run price changes on both the ETF and cash index are high. There are concerns that noise ETF trades will also lead the cash index. However, uninformed trade of SPY will impact the SPY price and possibly lead the cash index price temporarily, but there will be no permanent price impact. After an uninformed trade, there are two plausible consequences by the market. First, the cash market is too deep to be altered, so that the SPY price will revert to the cash index price without any impact on SPX. Second, SPX will follow SPY but other arbitrageurs will notice this uninformed trade on SPY and take an opposite trade on SPY. Then, SPY price will drop to the original level and lead the cash index again. Consequently, the long-run response function will be identically
zero in both of these two scenarios because the price level eventually moves to the origin. Another concern is that information may first be revealed in markets other than the ETF market, i.e. the S&P 500 futures market. [Hasbrouck (2003)] documents the fact that E-mini futures contracts (ES) led the ETF (SPY). Nevertheless, as shown in Figure 3 E-minis are led by either SPY or SPX, so that the futures contracts do not lead the market at all.

To investigate the impact of SPY trading activities on the cash index, we regress SPX intraday volatility on SPY trading volume, as well as a interaction term of SPY trading volume and the aforementioned indicator, $I_{ETF}$. Under the null hypothesis that noise trades will generate the same impact on cash index volatility as informed trades, the coefficient in front of the interaction term would be indifferent from zero.

Table 4 reports the results based on a basket of regressions where we regress cash index volatility on contemporaneous intraday SPY trading volume. The main regression reads as:

$$volatility_t = \beta \text{volume}_t + \gamma \text{volume}_t \times I_{ETF} + \alpha_{date} + \alpha_{hour} + \epsilon_t,$$

where $volatility_t$ is the uncentered mean square of second-by-second cash index returns (in basis points, 0.01%) during period $t$, $\text{volume}_t$ is the logarithm of average SPY share trading volume over period $t$, $\alpha_{hour}$ is hour dummy, and $\alpha_{date}$ is date dummy. $t$-statistics are computed based on standard errors clustered by date according to Petersen (2009). The granularity for constructing $volatility_t$ and $\text{volume}_t$ is 60 seconds, or 600 seconds. $I_{ETF}$ is an indicator equal to one when SPY leads SPX during the corresponding trading day. Under the null hypothesis that both informed and uninformed ETF trades have homogeneous impact on the cash index volatility, we should expect $\gamma$ to be zero. Regardless of the choice of granularity, the results convey the same information. The interaction term absorbs a significant amount of explanatory power from the univariate benchmark model where we regress $volatility_t$ on $\text{volume}_t$ only.

In Panel A of Table 4 where the granularity is 600 seconds, the benchmark model yields a coefficient $\hat{\beta}$ equal to 0.14. A standard deviation of $\text{volume}_t$ in 600 seconds,
which is 0.70, will impact the one-second variance of 0.09 \((\text{bps}^2)\). This impact is not economically negligible as the overall mean and standard deviation of \(\text{volatility}_t\) is 0.09 and 0.22 \((\text{bps}^2)\). When adding the interaction term, \(\hat{\beta}\) drops to 0.11, and the coefficient term in front the interaction term \(\hat{\gamma}\) is equal to 0.05. However, the significance level of \(\hat{\beta}\) drops dramatically and \(\hat{\gamma}\) is not significant at all. A plausible reason is due to the perfect multicollinearity, condition on \(I_{ETF}\) equals to one. The point estimates of \(\hat{\beta}\) and \(\hat{\gamma}\) suggest that, when informed traders are pervasive, trades on SPY have a stronger impact than on other days. Although the coefficient in front of \(I_{ETF}\) is \(-0.41\), it does not imply that SPX volatility is lower when SPY leads SPX. \(volume_t\) has an unconditional mean of 8.02, which almost cancels out the effect provided that \(\hat{\gamma}\) is equal to 0.05.

The panel specification raises omitted variable issue since market environments are different over trading days. The estimates of \(\hat{\beta}\) and \(\hat{\gamma}\) may be largely driven by the variation across different trading days, and \(volume_t\) is correlated with other variables representing market conditions.

To relieve this concern, we add date and hour fixed effects in our main specification. In the presence of both date and hour fixed effects, \(\hat{\beta}\) drops to 0.04 from 0.11. As reasoned above, \(\hat{\beta}\) of 0.11 from the specification without fixed effects mainly explains the variation between trading days. However, \(\hat{\gamma}\) retains the previous value, and slightly increases to 0.06. Considering the effect of SPY trading volume within a day, \(\hat{\gamma}\) is even greater than \(\hat{\beta}\). Moreover, \(t\)-statistic of \(\hat{\gamma}\) increases and \(\hat{\gamma}\) is significantly different from zero at 1\% significance level. Panel B of Table 4 exhibits the results based on a granularity of 60 seconds. In line with unreported results where we choose granularities from 30 seconds up to 3,600 seconds, our results remain invariant in terms of absolute value. Overall, the evidence in Table 4 points to the conclusion that noise traders indeed have impact on the underlying cash index but the impact is not as strong as informed trades.

### 5.2 Predictive Evidence

If arbitrage activities on noise trades are smoothly performed, we should expect ETF trading activities have lasting impacts on the volatility of the underlying cash index after
the trades are conducted. Also, informed trading activities may be correlated with cash
index volatility in two manners. First, informed traders’ private information may be
learned by the public in the future so that market will fluctuate once the information
is publicly revealed. Second, informed traders may exploit their information smoothly
and trade small amounts consecutively as modeled in [Kyle, Obizhaeva, and Wang (2014)].
Both channels suggest that current ETF trades may predict future cash index volatility.

To investigate the predictive ability of ETF trading activities on the underlying cash
index, we perform two predictive regressions and report the results in Table 5. Panel A
of Table 5 reports the results based on a benchmark regression:

\[ \text{volatility}_{t+s} = \beta \text{volume}_t + \alpha_{date} + \alpha_{hour} + \epsilon_{t+s}, \]

where \( \text{volatility}_{t+s} \) is the uncentered mean square of second-by-second cash index returns
during the \( s \)-th period ahead of period \( t \), \( \text{volume}_t \) is the logarithm of average SPY share
trading volume during period \( t \), \( \alpha_{hour} \) is hour dummy and \( \alpha_{date} \) is date dummy. \( t \)-statistics
are computed based on standard errors clustered by date according to [Petersen (2009)].
Reported coefficients of \( \hat{\beta} \)s are in multiples of \( 10^{-2} \). When predicting SPX volatility one
period ahead (\( s=1 \)) with a granularity of 30 seconds per period, the coefficient in front of
\( \text{volume}_t \) is equal to 3.31, statistically significant at 1% significance level. After expanding
the forecast horizon up to 36 periods (1,080 seconds or 18 minutes), the forecasting power
decays to 1.18, despite the fact that it remains statistically significant. In Panel B, the
predictive regression is augmented by the interaction term and reads as:

\[ \text{volatility}_{t+s} = \beta \text{volume}_t + \gamma \text{volume}_t \times I_{ETF} + \alpha_{date} + \alpha_{hour} + \epsilon_{t+s}, \]

where \( \hat{\gamma} \)s are also reported in multiples of \( 10^{-2} \). When predicting SPX volatility one
period ahead, \( \hat{\beta} \) drops to 1.38, compared with the benchmark model where \( \hat{\beta} \) is 3.31. However,
\( \hat{\gamma} \) is equal 3.93, both statistically and economically significant. The predictive power of
SPY trades is more than tripled\(^\text{12}\) during days when SPY leads SPX. When the prediction
window is expanded to three periods (\( s=3 \), or 90 seconds), \( \hat{\beta} \) shrinks to 0.69, about half

\(^{12}(3.93 + 1.38)/1.38 \approx 3.8\)
of the one period $\hat{\beta}$. On the contrary, $\hat{\gamma}$ decreases slowly to 3.33. It takes up to 36 periods (1,080 seconds) for $\hat{\gamma}$ decays to 2.36, two-thirds of its one period level. This evidence indicates that noise trades on SPY have a less persistent impact on the volatility of SPX, decaying as much as 10 times faster. In Panel C, we reports the predictive regression results based on a granularity of 100 seconds. A similar pattern shows up such that $\hat{\gamma}$ has a much slower decaying speed. In Figure 4, we visualize the estimates of $\hat{\beta}$s and $\hat{\gamma}$s based on the same augmented predictive regression under the three choices of granularities (30, 60, 100 seconds) and a collection of forecasting periods from $s = 1$ to $s = [50, 25, 15]$ such that the maximum forecasting calendar time is 1,500 seconds. The plots are consistent with the evidence in Table 5. Both $\hat{\beta}$s and $\hat{\gamma}$s are parallel under different choices of granularities, suggesting that the predictive power of ETF trades decays as calendar time passes and is invariant of granularity choices. The predictive power of noise trades $\hat{\beta}$ turns to be insignificant shortly after approximately 100-200 seconds. On the contrary, $\hat{\gamma}$s are slow moving and persistent. The lines representing the lower bound of 90% confidence interval of $\hat{\gamma}$s merely touch the x-axis at 1,500 seconds. As informed trades may contain information related to the state of future, it is not surprising that their impact would last longer. Although our evidence is not sufficient to identify the causal relationship between informed ETF trades and future underlying volatility, it does indicate that the impact of uniformed trades generally decay much faster and have insignificant impact with SPX volatility after a interval 100 to 200 seconds.

6 Conclusion

As a rapid rising class of exchange traded securities, ETFs have drawn the attention of both regulators and academics. For all the benefits that ETFs bring to investors, people have concerns that this class of products might destabilize underlying cash markets. That is, ETFs possibly introduce a new layer of demand shocks, which might be propagated into the underlying cash market.
An econometric issue is the difficulty of identifying informed and uninformed trading volume. Therefore, it is not clear whether an increase of cash index volatility following a surge of ETF trading volume should be attributed to a price discovery channel, or a noise propagation channel. In this paper, we investigate the lead-lag effect between ETF and the underlying cash index. Since noise trades have no impact on the fundamental in the long-run, we obtain a measure for the density of informed trading activities based on a long-run response function. This measure allows us to access the marginal impact of a noise trade or an informed trade on the underlying cash index volatility.

Then, we test the relation between intraday ETF trading activities and the underlying cash index. Based on the data of Standard & Poor’s Depository Receipts (SPDR, ticker: SPY) and the S&P 500 index (ticker: SPX), we show that noise trades do have an impact (but much weaker than the informed trades do) on contemporaneous volatility of the underlying cash index. Moreover, noise trades lose the predictive power for the cash index in merely three minutes.
Table 1: Summary statistics of SPY trades and one-second variance of ES, SPX, and SPY. This table reports the summary statistics for SPY trading volume and one-second variance of E-mini futures (ES), S&P 500 Index (SPX), and SPDR S&P 500 ETF Trust (SPY). In Panel A, we report summary statistics for the logged SPY share trading volume. We average trading volume per second within a 600 seconds window. Reported are the mean and standard deviation of this quantity. In addition, we compute the standard deviation of SPY trading volume within each trading day. The next two columns report the mean and the standard deviation of this within variation. In Panel B, we summarize the variation of one-second returns for ES, SPX, and SPY. We first compute the variance of one-second returns within each trading day. Reported are summary statistics charactering the intraday variances. Data are obtained from Bloomberg and the sample starts on Mar 03, 2015 and ends on Sep 17, 2015.

<table>
<thead>
<tr>
<th>Panel A: SPY (log) Share Trading Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>600 Seconds</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Variance of One-Second Returns (in $bps^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$bps^2$</td>
</tr>
<tr>
<td>$\Delta p_t^{ES}$</td>
</tr>
<tr>
<td>$\Delta p_t^{SPX}$</td>
</tr>
<tr>
<td>$\Delta p_t^{SPY}$</td>
</tr>
</tbody>
</table>
Table 2: Autocorrelation of ES, SPX and SPY. Within each trading day, we compute the correlation between $\Delta p_t$ and $\Delta p_{t-s}$, where $p_t$ is a vector which includes log prices of E-mini (ES), S We calculate the contemporaneous correlation ($s = 0$) and autocorrelation up to 30-second. Reported are the mean and standard deviation of the correlation coefficients across all the trading days. Data are obtained from Bloomberg and the sample starts on Mar 03, 2015 and ends on Sep 17, 2015.

<table>
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<tr>
<th></th>
<th>$s = 0$</th>
<th>$s = 1$</th>
<th>$s = 3$</th>
<th>$s = 5$</th>
<th>$s = 10$</th>
<th>$s = 20$</th>
<th>$s = 30$</th>
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<tr>
<td>$\Delta p_t^{ES}$</td>
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<td>-12.59</td>
<td>-1.48</td>
<td>-0.26</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>$\Delta p_t^{SPX}$</td>
<td>55.53</td>
<td>1.20</td>
<td>0.10</td>
<td>0.27</td>
<td>-0.02</td>
<td>-0.06</td>
<td>0.14</td>
</tr>
<tr>
<td>$\Delta p_t^{SPY}$</td>
<td>67.10</td>
<td>-0.13</td>
<td>-0.12</td>
<td>0.22</td>
<td>0.03</td>
<td>0.07</td>
<td>0.16</td>
</tr>
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</table>
Table 3: Impulse response functions among E-mini future, ETF and the underlying cash index. This table reports the summary statistics for the impulse response functions based on a VECM suggested by Hasbrouck (2003). We perform VECM and compute the impulse response functions on each trading day, respectively. Reported are the summary statistics characterizing the distribution of the daily impulse response functions. Panel A reports the results based on a VECM including two price series: E-mini future (ES) and SPDR S&P 500 ETF Trust (SPY). Panel B exhibits the results based on S&P 500 Index (SPX) and SPY. Panel C presents the results for a VECM including all three series. When performing VECM, we include lagged second-by-second price differences up to 300 seconds. We rely on Polynomial Distributed Lags (PDL’s) to constrain the coefficients in front of the lagged terms in order to reduce the number of parameters needed to be estimated. The impulse response function represents the long run price movement following one unit shock from a single price series. In practice, we define long run as the passage of 600 seconds. Our results are based on Bloomberg intraday data from Mar 04, 2015 to Sep 17, 2015.

<table>
<thead>
<tr>
<th>Panel A: VECM with ES and SPY</th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Ticker</td>
<td>Mean</td>
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<td>Min</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>Max</td>
</tr>
<tr>
<td>ES</td>
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<td>0.17</td>
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<td>0.12</td>
<td>0.21</td>
<td>0.30</td>
<td>0.77</td>
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<tr>
<td>SPY</td>
<td>0.81</td>
<td>0.19</td>
<td>0.37</td>
<td>0.69</td>
<td>0.80</td>
<td>0.91</td>
<td>1.70</td>
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</table>

<table>
<thead>
<tr>
<th>Panel B: VECM with SPX and SPY</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Ticker</td>
<td>Mean</td>
<td>Std</td>
<td>Min</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>Max</td>
</tr>
<tr>
<td>SPX</td>
<td>0.67</td>
<td>0.39</td>
<td>-0.12</td>
<td>0.38</td>
<td>0.64</td>
<td>0.94</td>
<td>1.60</td>
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<tr>
<td>SPY</td>
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<td>0.25</td>
<td>0.01</td>
<td>0.48</td>
<td>0.66</td>
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<table>
<thead>
<tr>
<th>Panel C: VECM with ES, SPX and SPY</th>
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<th></th>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Ticker</td>
<td>Mean</td>
<td>Std</td>
<td>Min</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>Max</td>
</tr>
<tr>
<td>ES</td>
<td>0.13</td>
<td>0.17</td>
<td>-0.67</td>
<td>0.05</td>
<td>0.13</td>
<td>0.21</td>
<td>0.69</td>
</tr>
<tr>
<td>SPX</td>
<td>0.58</td>
<td>0.38</td>
<td>-0.20</td>
<td>0.29</td>
<td>0.55</td>
<td>0.83</td>
<td>1.62</td>
</tr>
<tr>
<td>SPY</td>
<td>0.57</td>
<td>0.25</td>
<td>0.01</td>
<td>0.38</td>
<td>0.57</td>
<td>0.73</td>
<td>1.33</td>
</tr>
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Table 4: Do informed trades and noise trades on SPY have heterogeneous impact on index volatility? This table reports the evidence based on a basket of regressions where we regress cash index volatility on intraday SPY trading volume. The main regression reads as: \( \text{volatility}_t = \beta \text{volume}_t + \gamma \text{volume}_t \times I_{ETF} + \alpha_{date} + \alpha_{hour} + \epsilon_t \), where \( \text{volatility}_t \) is the uncentered mean square of second-by-second cash index returns during period \( t \), \( \text{volume}_t \) is the logarithm of SPY share trading volume per second, \( \alpha_{hour} \) is hour dummy, and \( \alpha_{date} \) is date dummy. The granularity for constructing \( \text{volatility}_t \) and \( \text{volume}_t \) is 60 seconds, or 600 seconds. \( I_{ETF} \) is an indicator equal to one when SPY is leading SPX during the corresponding trading day. Our results are based on Bloomberg intraday data from Mar 04, 2015 to Sep 17, 2015.

<table>
<thead>
<tr>
<th>Granularity</th>
<th>PanelA : 600 seconds</th>
<th>PanelB : 60 seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>-1.06*** -0.83*</td>
<td>-0.84*** -0.62*</td>
</tr>
<tr>
<td></td>
<td>-4.55 -1.70</td>
<td>-5.03 -1.91</td>
</tr>
<tr>
<td>( \text{volume} )</td>
<td>0.14*** 0.11* 0.13* 0.04***</td>
<td>0.12*** 0.09** 0.09** 0.04***</td>
</tr>
<tr>
<td></td>
<td>4.76 1.77 1.88 4.17</td>
<td>5.27 1.99 2.00 5.89</td>
</tr>
<tr>
<td>( \text{volume} \times I_{ETF} )</td>
<td>0.05 0.05 0.06***</td>
<td>0.05 0.05 0.06***</td>
</tr>
<tr>
<td></td>
<td>0.75 0.73 2.70</td>
<td>1.08 1.08 3.27</td>
</tr>
<tr>
<td>( I_{ETF} )</td>
<td>-0.41 -0.41</td>
<td>-0.41 -0.41</td>
</tr>
<tr>
<td></td>
<td>-0.76 -0.76</td>
<td>-1.10 -1.11</td>
</tr>
<tr>
<td>( \alpha_{date} )</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \alpha_{hour} )</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \text{Cluster(date)} )</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( N )</td>
<td>5343 5343 5343 5343</td>
<td>53430 53430 53430 53430</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>19.64 20.28 22.01 45.65</td>
<td>13.33 14.08 14.77 31.69</td>
</tr>
</tbody>
</table>
Table 5: Can informed trades and noise trades on SPY predict index volatility? This table reports the evidence based on the predictive regressions. Panel A reports the results based on a benchmark regression: $\text{volatility}_{t+s} = \beta \text{volume}_{t} + \alpha_{date} + \alpha_{hour} + \epsilon_{t+s}$, while Panels B and C report the results based on the augmented regression: $\text{volatility}_{t+s} = \beta \text{volume}_{t} + \gamma \text{volume}_{t} \times I_{ETF} + \alpha_{date} + \alpha_{hour} + \epsilon_{t+s}$. $\text{volatility}_{t+s}$ is the uncentered mean square of second-by-second cash index returns during the $s$-th period ahead of period $t$, $\text{volume}_{t}$ is the logarithm of SPY share trading volume per second during period $t$, $\alpha_{hour}$ is hour dummy, and $\alpha_{date}$ is date dummy. Reported coefficients $\beta$ and $\gamma$ are in multiples of $10^{-2}$. The granularity for each period is 30 seconds, or 100 seconds. $I_{ETF}$ is an indicator equal to one when SPY is leading SPX during the corresponding trading day. Our results are based on Bloomberg intraday data from Mar 04, 2015 to Sep 17, 2015.

<table>
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<tr>
<th>Granularity</th>
<th>Panel A: 30 seconds</th>
<th>Panel B: 30 seconds</th>
<th>Panel C: 100 seconds</th>
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</thead>
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<tr>
<td>Forecasting periods(s)</td>
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<td>3</td>
<td>36</td>
</tr>
<tr>
<td>$\text{volume} (10^{-2})$</td>
<td>3.31***</td>
<td>2.33***</td>
<td>1.18***</td>
</tr>
<tr>
<td>$\text{volume} \times I_{ETF} (10^{-2})$</td>
<td>6.17</td>
<td>4.74</td>
<td>3.37</td>
</tr>
<tr>
<td>$\alpha_{date}$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>$\alpha_{hour}$</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
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<td>Yes</td>
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</tr>
<tr>
<td>$N$</td>
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<td>101928</td>
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<tr>
<td>$R^2$</td>
<td>24.60</td>
<td>24.24</td>
<td>23.23</td>
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</table>
Figure 1: Monthly trading activity for S&P 500 index stocks, aggregate S&P 500 ETFs, and largest three ETFs. This figure reports the monthly trading volumes for the stocks in S&P 500 index and the ETFs whose underlying securities are S&P 500 index stocks. Aggregate ETFs trading volume is the sum of dollar trading volumes for all the S&P 500 ETFs. We define S&P 500 ETFs as ETFs whose dollar holdings of S&P 500 stocks consist more than 90% of the ETF’s total assets under management. We also report the trading volume for three individual ETFs which have the largest trading volume during the entire sample. All results are computed based on data from CRSP between 01/2000 and 12/2014.
Figure 2: Monthly trading activity for S&P 500 index stocks, SPDR S&P 500 ETF, and futures. This figure reports the monthly trading volumes for the stocks in S&P 500 index, SPDR S&P 500 ETF (SPY), E-mini S&P 500 Futures (ES), and S&P 500 Futures (SP). Stocks and ETF results are computed based on data from CRSP between 01/2000 and 12/2014. Future data are obtained from Wiki Continuous Futures on Quandl.com.
Figure 3: Impulse response functions among E-mini future, ETF and the underlying cash index. This figure presents the evolution of daily impulse response functions based on a VECM suggested by Hasbrouck (2003). The VECM includes three price series: E-mini future (ES), SPDR S&P 500 ETF Trust (SPY) and S&P 500 Index (SPX). The following three panels highlight each individual series, respectively. We include lagged second-by-second price differences up to 300 seconds. We lie on Polynomial Distributed Lags (PDLs) to constrain the coefficients in front of the lagged terms in order to reduce the number of parameters needed to be estimated. The impulse response function represents the long run price movement following one unit shock from an individual price series. In practice, we define long run as the passage of 600 seconds. Our results are based on Bloomberg intraday data from Mar 04, 2015 to Sep 17, 2015.
Figure 4: Can informed trades and noise trades predict index volatility? This table reports the evidence based on the predictive regressions: \[ \text{volatility}_{t+s} = \beta \text{volume}_t + \gamma \text{volume}_t \times I_{ETF} + \alpha_{date} + \alpha_{hour} + \epsilon_{t+s}, \]

where volatility\(_{t+s}\) is the uncentered mean square of second-by-second cash index returns during the \(s\)-th period ahead of period \(t\), volume\(_t\) is the logarithm of SPY share trading volume per second during period \(t\), \(\alpha_{hour}\) is hour dummy, and \(\alpha_{date}\) is date dummy. The solid lines are estimates of \(\beta\) and \(\gamma\) for a variety of choices of granularity and forecasting windows, while dotted lines are 90% confidence intervals. For each granularity, we choose the forecasting window \(s\) such that the maximum forecasting calendar time is up to 1,500 seconds. We forecast up to 50, 25, or 15 periods ahead for the granularity of 30, 60, or 100 seconds. Our results are based on Bloomberg intraday data from Mar 04, 2015 to Sep 17, 2015.
References


