Predicting ETF Liquidity

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Abstract

A substantial amount is incurred in ETF transaction costs each year. This paper examines a vector autoregressive (VAR) model's performance and other trading schedules to time trades in a large sample of 1,350 ETFs over the 2011 to 2017 period. We find varied spread savings for large and retail ETF traders by timing transactions. A large ETF trader can save 7.40% of ETF spread costs, whereas trading at the market closing time would be optimal for a retail ETF trader to reduce spread costs. The spread savings for large ETF traders are diverse across ETF sectors and depend on the spread volatility.

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1. Introduction

Transaction costs are an essential determinant of investors' returns (e.g., French, 2008). As a result, several papers have investigated approaches to minimizing spread costs in stock transactions (Taylor, 2002; Wald and Horrigan, 2005; Groß-KlußMann and Hautsch, 2013). In this paper we contribute to the literature by considering the extent to which traders can minimize transaction costs in trading ETFs via a systematic trading schedule, which is essential for several reasons.

First, ETFs are an important and growing component of financial trading. According to Financial Times, by 2016, ETFs accounted for approximately 30 percent of all U.S. equity trading by value[1]. The average daily transaction value of U.S. ETFs was USD 110.79 billion[2] as of Q3 2020. Second, high-frequency trading has become prevalent for ETFs due to low transaction costs and information availability (Ben-David, Franzoni, and Moussawi, 2014). As high-frequency traders trade a lot with marginal expected gain for each trade, minimizing ETF bid-ask spread should be their key priority. Third, while some ETFs have low bid-ask spreads, which are likely to have little impact on ETF investors, many ETFs do not. The ETF bid-ask spreads in our sample are diverse, ranging from 0.03% at the 1st percentile to 4.42% at the 99th percentile with an average of 0.44%[3]. The cost of trading ETFs is an essential component of the return many ETF investors receive.

Furthermore, although investors can pick an ETF with a low bid-ask spread among different ETFs tracking the same index, this strategy is not without cost. Khomyn, Putniņš, and Zoican (2020) find that an ETF with greater market liquidity tends to charge higher

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[1] Financial Times (2017). ETFs are eating the US stock market. *Retrieved from*: https://www.ft.com/content/6dabad28-e19c-11e6-9645-c9357a75844a.

[2] *Retrieved from*: https://www.nyse.com/etf/exchange-traded-funds-quarterly-report

[3] For comparison, the average bid-ask spread of US stocks listed on NYSE, NASDAQ and AMEX between 2003 and 2015 is 0.82% as shown in Abdi and Ranaldo (2017). Bid-ask spreads of several foreign exchanges range from 0.03% to 0.2% as of 2012 (Blackrock, 2012).

management fees than its peers. Finally, while institutional or large investors may access authorized participants who can create or redeem ETF shares at low transaction costs, recent statistics indicate that creation/ redemption activities account for only a small part of ETF market turnover. According to Bloomberg, the average daily creation/redemption activities of U.S. ETFs are around USD 15 billion in 2020, whereas their daily trading volume is about USD 150 billion[3]. Given the above reasons, reducing transaction costs is a crucial topic for ETF investors.

We use an unrestricted vector autoregressive (VAR) model based on Taylor's (2002) model to predict intraday ETF bid-ask spreads for a large sample of 1,350 U.S. ETFs between January 2011 and December 2017. In our VAR model, we assume ETF bid-ask spread is dependent on its past spread, past degree of return volatility, past level of trade volume, and past level of trade intensity. These trading characteristics are essential determinants of ETF liquidity, as documented in Agrrawal and Clark (2009), Camalia, Deville, and Riva (2013), and Ivanov (2017). We find that this model is superior to a moving average model in predicting short-term ETF bid-ask spreads. Moreover, splitting and timing trades based on predictions from this model brings meaningful transaction cost savings for large ETF traders compared to the other trading schedules.

We assess the VAR model's quality by considering the spread forecasts' deviation relative to the actual figures. Using Mariano and Diebold's (1995) test and Harvey, Leybourne, and Newbold's (1997) test, we find that the VAR model generates better forecasts than a moving average prediction model. Furthermore, we find the model's performance is dependent on ETF characteristics and macro-economic conditions. The ETF characteristics, sector, and style affect the spread forecast accuracy. Forecast errors are broader when an ETF is more

[3] *Retrieved from*: https://www.etftrends.com/esg-channel/how-investors-turned-to-etfs-for-liquidity-and-market-access-in-2020/.

volatile in return and smaller in size. The VAR model produces better forecasts for ETFs belonging to the Allocation and Fixed Income sectors. Among equity ETFs, the VAR model has lower forecast errors for ETFs investing in large-cap stocks.

The predictability of a forecasting model might be dependent on macro-economic conditions in certain periods (Fama and French, 1989; Schwert, 2002). Using a set of macro-economic variables representing market-wide uncertainty and financial risk, we find that those factors impact the ability to predict ETF bid-ask spreads using the VAR model. The model's forecast errors increase with market uncertainty measured by the range of market return and market return volatility. Moreover, an increase in default risk in the market also dampens forecast accuracy.

We also estimate the economic significance of this VAR model from the perspective of both large and retail ETF traders[4] who use its bid-ask spread predictions to time their trades. The average executed bid-ask spread of a hypothetical ETF trader using bid-ask spread forecasts from the VAR model to schedule her trade is compared to that using other trading schedules. For a large ETF trader who wants to hide her trade motivation by splitting the orders over the trading day, the VAR trading schedule is superior to other trading schedules in terms of spread saving. We find that the average executed bid-ask spread using the VAR model to schedule trade is 7.4% and 8.29% lower than that using a time-weighted average price (TWAP) trading schedule and a moving average trading schedule, respectively. The spread discount for a large ETF trader using the VAR trading schedule is as high as 30.81% compared to the daily average bid-ask spread of ETFs. However, we reveal that trading would be optimal to reduce bid-ask spread cost once at the close for a retail ETF trader who does not need to split his order. ETFs' average closing bid-ask spread is 45% lower than the average executed bid-ask spread

[4] We define a large ETF trader as traders who trade substantial ETF shares for either liquidity reasons or possessing private information. Retail ETF trader is defined as traders who trade a small number of ETF shares and do not have private information.

using the VAR trading schedule. Nevertheless, there is a non-execution risk for orders submitted at the market close.

The spread saving of the VAR trading schedule compared to the TWAP trading schedule for ETFs is lower than that for stocks as documented by Taylor (2002) and Groß-KlußMann, and Hautsch (2013)[5]. We expect that spread volatility can partly explain why the transaction cost savings by splitting and timing trades are lower for ETFs than stocks. If bid-ask spreads are unchanged throughout the day, there is no need to save spread costs by timing transactions. Expected spread savings by timing trades should be dependent on spread volatility. ETFs are diversified portfolios where company-specific risks are canceled out, ETFs should have lower volatility in return and spread than stocks. We find that spread volatility is positively correlated with spread saving, which supports our explanation. Furthermore, while the average spread saving is low, it is widely diverse across ETF sectors. The benefit of timing trades is lower for less volatile ETF sectors like Fixed Income, and Tax Preferred while higher for more volatile ETF sectors such as Equity and Commodities.

Our research makes several contributions to the current literature of ETF liquidity. First, our present work is the first to predict ETF liquidity to the best of our knowledge. Compared to individual securities, ETFs provide lower trading costs and have lower information asymmetry (Hedge and McDermott, 2004; Chelley-Steeley and Park, 2010). Deriving a model to predict intraday ETF liquidity could bring crucial implications for market participants. For portfolio managers, better forecasts of expected trading costs improve the capacity to implement portfolio strategies and monitor trade execution quality. Traders, especially high-frequency traders, can take advantage of mispricing in the ETF market, even if these inefficiencies last for just a few minutes or seconds. As high-frequency traders tend to trade a

[5] Taylor (2002) finds that using predictions of bid-ask spreads from a VAR model can save up 34% of spread costs for LSE stocks. Groß-KlußMann and Hautsch (2013) use a long-memory autoregressive conditional Poison model to predict the bid-ask spreads of 4 US mid-cap stocks and find that the predictions from their model can help traders saving 8.4% to 10.9% of spread costs.

lot, they are concerned with transaction costs, and forecasting ETF liquidity should be prominent.

Second, our research examines the degree to reduce the ETF transaction costs using ETF bid-ask spread predictions. We find the VAR model helps large ETF traders save their spread costs compared to other trading schedules. However, it is optimal for retail ETF traders to trade at the close to minimize spread costs. The benefit of splitting and timing trades using the VAR trading schedule compared to using TWAP trading schedule tends to be lower for less volatile ETF sectors like Fixed Income, and Tax Preferred while higher for more volatile ETF sectors such as Equity and Commodities. Our finding of a positive relationship between transaction cost-saving and spread volatility is new to the literature. It provides unique insight for traders and researchers looking to minimize ETF transaction costs.

Third, our research investigates the effect of ETF characteristics and market-wide uncertainties on the VAR model's forecast accuracy. Some ETF sectors like Allocation or Fixed Income have lower forecast errors than others when using the VAR model to predict their intraday bid-ask spreads. The dependency of the forecast errors on ETF and market-wide volatility also highlights this prediction model's limitations. When liquidity has a great chance of dry up in the market, predictions of ETF intraday liquidity using the VAR model are less reliable.

The remainder of the paper is structured as follows. Section 2 reviews related literature. Section 3 is about data and methodologies used in this paper. Section 4 documents the empirical results of using the VAR model to predict ETF bid-ask spreads. Section 5 concludes the article.

2. Literature review

While literature is replete with research on liquidity, predicting liquidity receives lesser attention. Huang and Stoll (1994) indicate the price impact of trading stocks using a two-equation econometric model. They assume that quote return is a function of several factors, including past quote return, market return, and inventory change. Breen, Hodrick, and Korajczyk (2002) predict the price impact of trading stocks based on net turnover[6]. They find that the coefficient of the price impact in their model is dependent on the adverse selection cost, the non-information-based costs of market making, and the extent of shareholder heterogeneity of stocks.

In terms of predicting bid-ask spreads, Huang and Masulis (1999) use a trivariate VAR to model bid-ask spread, competition, and return volatility in foreign exchange markets. Based on Huang and Masulis's (1999) framework, Taylor (2002) develops an unrestricted VAR model to predict quoted bid-ask spreads of stocks on the London Stock Exchange. In this model, Taylor expects the stock bid-ask spread as a function of five lagged factors. These determinants are lagged bid-ask spread, dealer competition, return volatility, trading volume, and trade intensity. Taylor (2002) demonstrates that his model can efficiently project bid-ask spreads of stocks and save transaction costs by about 34% for traders. Recently, Groß-KlußMann and Hautsch (2013) use a long-memory autoregressive conditional Poison model to predict the bid-ask spreads of 4 U.S. mid-cap stocks and find that the predictions from their model can help traders saving 8.4% to 10.9% of spread costs.

Variables used to predict stock bid-ask spread in Taylor's (2002) model are well-known in microstructure literature to affect stock liquidity. For instance, Stoll (2000) explains stock liquidity variation on several stock trading characteristics, including return volatility, dollar-trading volume, and the number of trades. Regarding intraday liquidity, McInish and Wood

[6] Breen et al (2002) define Net turnover as buyer-initiated volume less seller-initiated volume as a fraction of shares outstanding

(1992) develop a model to explain intraday stock bid-ask spread based on intraday trading activity, intraday risk level (stock volatility), the amount of information coming to the market, and the level of competition. Lee, Mucklow, and Ready (1993) study the effect of volume on the stock depth and spread using intraday data. They find that higher volume during a given interval should be associated with a broader spread and lower depth at the end of the interval during a trading day.

Like stock bid-ask spread, the ETF bid-ask spread varies with its trading characteristics. Agrrawal and Clark (2009) find that the ETF bid-ask spread inversely correlates with trading volume and market capitalization. Camalia, Deville, and Riva (2013) reveal that ETF bid-ask spread decreases with the ETF trading volume and increases with ETF return volatility. Ivanov (2017) documents that factors including trading activity, risk, information, and competition influence ETF intraday bid-ask spread using high-frequency data. These findings support that the variables used in Taylor's (2002) model could be useful to predict ETF liquidity.

3. Data and Methodologies

3.1. Data

We conduct our research using intraday data of 1,350 U.S. ETFs during the period between 2011 and 2017. First, we obtain data on all exchange-traded funds from the CRSP stock database identified by their share code of 73. Then we extract intraday trading data of these ETFs from Thomson Reuters Tick History (TRTH). To be consistent with prior literature when studying stocks' intraday activities, we examine ETFs' trading activity between 9:30 am to 4:00 pm.

To screen intraday data files for mistakes, we employ a similar screening procedure used previously by Huang and Stoll (1996) and Bessembinder (1999). We exclude:

- Quotes if either the ask or bid price is less than or equal to zero;

- Quotes if either the ask size or bid size is less than or equal to zero;

- Quotes if the bid-ask spread is less than zero;

- Quotes and trades before the open and after the close;

- Trades if the price or volume is less than or equal to zero;

- The trade price, p_t, if $|(p_t - p_{t-1})/p_{t-1}| > 0.5$;

- The ask price, a_t, if $|(a_t - a_{t-1})/a_{t-1}| > 0.5$;

- The bid price, b_t, if $|(b_t - b_{t-1})/b_{t-1}| > 0.5$.

We source other ETF characteristics using data from CRSP and Morningstar. We get daily and the monthly bid-ask spread, trading volume, price, return, and shares outstanding of ETFs from CRSP. Qualitative characteristics such as ETF sectors and investment categories are from Morningstar.

3.2. Methodologies

We use Taylor's (2002) model framework to predict the quoted bid-ask spread of 1,350 ETFs from 01 Jan 2011 to 29 December 2017. Following Taylor's (2002) model, we also use a frequency of 5 minutes to calculate variables in the VAR model. We estimate the following VAR model:

$$\begin{pmatrix} s_{i,t} \\ \sigma_{i,t} \\ V_{i,t} \\ I_{i,t}^{T} \end{pmatrix} = \begin{pmatrix} \beta_1(L) & \beta_2(L) & \beta_3(L) & \beta_4(L) \\ \beta_5(L) & \beta_6(L) & \beta_7(L) & \beta_8(L) \\ \beta_9(L) & \beta_{10}(L) & \beta_{11}(L) & \beta_{12}(L) \\ \beta_{13}(L) & \beta_{14}(L) & \beta_{15}(L) & \beta_{16}(L) \end{pmatrix} \begin{pmatrix} s_{i,t-1} \\ \sigma_{i,t-1} \\ V_{i,t-1} \\ I_{i,t-1}^{T} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,i,t} \\ \epsilon_{2,i,t} \\ \epsilon_{3,i,t} \\ \epsilon_{4,i,t} \end{pmatrix} \tag{1}$$

where $s_{i,t}$ is the quoted bid-ask spread of ETF i measured at the end of each 5-minute time interval starting from 9:35 am and ending at 4:00 pm of the trading day; $\sigma_{i,t}$ is the standard deviation of midpoint quotes during each 5-minute time interval[7]; $V_{i,t}$ is the trading volume during each 5-minute time interval; $I_{i,t}^{T}$ is the number of trades during each 5-minute time interval; $\beta_1(L)$ to $\beta_{16}(L)$ are lag polynomials each of order p, and $\epsilon_{k,i,t}$ is the error term.

Following Taylor's (2002), we impose a lag length equal to one trading day in the model[8] , and the remaining lag order is estimated using the Akaike information criterion (AIC). Upon completion of each estimation of the model, the model forecasts the liquidity at 1-step ahead (5 minutes head), 2-step ahead (10 minutes ahead), 3-step ahead (15 minutes ahead), 4-step ahead (20 minutes ahead), and 5-step ahead (25 minutes ahead).

Consistent with Taylor's (2002) model, we use de-meaned variables for Eq. (1). The de-meaned variables are the difference between the variables and their mean values over the sample period. The whole sample period starts at 9:30 am on 03 Jan 2011 and ends at 4:00 pm on 29 December 2017. Each day has 390 minutes of trading time that equals 78 5-minute time intervals. The first in-sample data used starts at 9:35 am on 03 Jan 2011 and ends at 4:00 pm on 07 Jan 2011. Estimating Eq. (1) using this sample data will generate bid-ask spread forecasts for 9:35 am, 9:40 am, 9:45 am, 9:50 am, and 9:55 am on 10 January. The second in-sample data starts at 10:05 am on 03 January and ends at 10:00 am on 10 January. Thus, the in-sample data is rolled over every 30 minutes with a fixed estimation window of 5 trading days.

4. Empirical Results

[7]. For instance, the first $\sigma_{i,t}$ of each day is calculated as the standard deviation of midpoint quotes between 9:30 am to 9:35 am

[8] This specification accounts for periodic components in the variables. As a trading day can be divided into 78 5-minute intervals, so we use a lag order of 78 in our VAR model to account for periodicity. Descriptive statistics of ETF quoted bid-ask spread and effective spread and the evidence of their periodicities can be found in Appendix A and Appendix B, respectively. Appendix C plots the intraday pattern of ETF quoted bid-ask spread and effective spread.

This section presents the empirical results of using the VAR model in predicting intraday ETF bid-ask spread. Sub-section 4.1 assesses the forecast quality of the model using various tests. Sub-section 4.2 examines the determinants of the model's forecast errors. Sub-section 4.3 gauges the economic benefit derived from a trading strategy based on the model's prediction results. Sub-section 4.4 investigates the effect of spread volatility on the spread saving derived from the VAR model.

4.1. Assessing forecast accuracy

The means of the variables used in Eq. (1) are shown in Table 1. Panel A shows these statistics by the ETF sector. Fixed Income has the lowest average bid-ask spreads among various ETF sectors, followed by Tax Preferred and Allocation. Conversely, Convertibles and Alternative have the highest average bid-ask spreads, respectively. In Panel B, we group ETFs into liquidity quintiles based on their average quoted bid-ask spreads. The mean bid-ask spread ranges from 22.52 basis points for the most liquid ETFs to 77.47 basis points for the least liquid ETFs.

[Insert Table 1 about here]

In Taylor's (2002) work, the VAR forecasts' quality is compared to predictions generated by a simple random walk model. He assumes that "the cumulative spreads follow a random walk while the spread itself is a white noise process with positive mean". Therefore, this model "generates forecasts equal to mean of the in-sample period spread" (Taylor, 2002, p. 807). Following Taylor's (2002) paper, we compare the mean squared forecast error (MSFE) and the mean absolute forecast error (MAFE) of the VAR model (M2) with this simple moving average model (M1). The formulas for MAFE and MSFE are the following:

$$MAFE=\frac{1}{T}.\sum_{t=1}^{T} | y_{t+h} - y'_{t+h} | \quad (2)$$

$$MSFE=\frac{1}{T}.\sum_{t=1}^{T} (y_{t+h} - y'_{t+h})^2 \quad (3)$$

where y_{t+h} is the h-step ahead forecast of ETF bid-ask spread at time t and y'_{t+h} is the realized value of the ETF bid-ask spread at the time ($t+h$).

Table 2 presents a summary of the comparison between forecast error metrics of M1 and M2. Panel A shows the proportion of ETFs with lower MAFE and MSFE using the VAR model than the moving average model. In general, both MAFE and MSFE comparisons indicate that using the VAR model, M2, generates better results than the moving average model, M1, for short-term forecasts (h=1, 2) for most ETFs. Consistent with Taylor's (2002) findings, we find that the VAR model's benefit to estimate bid-ask spreads for ETFs is most apparent under the 1-step forecasts and the MAFE criteria. In Panel A, 78.55% of ETFs in our sample exhibit lower MAFE when the VAR model predicts the next 5 minutes bid-ask spreads compared to the moving average model. The VAR model's outperformance remains relatively high for the 10-minute (i.e., 2-step) prediction horizon, with 70.29% of ETFs showing lower MAFE. The VAR model's performance relative to that of the moving average model in MAFE reduces substantially after the 2-step forecast. The results of MSFE are less impressive as only 54.2% of ETFs have lower MSFE using M2 versus M1 for 1-step ahead bid-ask spread prediction.

Table 2 Panel B shows the average values of MAFE and MSFE for M1 and M2. Overall, the average values of MAFE and MSFE for M2 are higher than for M1, except for the 1-step forecast ahead. The average MAFE at the 1-step horizon for M2 is 0.00145, approximately 56% smaller than for M1.

[Insert Table 2 about here]

To statistically test the predictive accuracy of M1 and M2-based forecasts, we first use the Diebold-Mariano test (1995), calculated through the following steps:

$$d=\frac{1}{N}\cdot\sum_{n=1}^{N}[\,g(e_{t+h}) - g(e'_{t+h})\,] \tag{4}$$

$$DM=\frac{d}{(\sigma_d^2/N)^{1/2}} \tag{5}$$

where $g(e_{t+h})$ and $g(e'_{t+h})$ are the loss functions of M1 and M2, respectively; N is the number of rolling out-of-sample forecasts; σ_d^2 is the variance of d and *D.M.* is the Diebold-Mariano statistic. We use Diebold-Mariano to test the null hypothesis that the VAR model forecasts, M2, are of the same or lower quality than forecasts from the moving average model, M1. The alternative is that forecasts from M2 are better than forecasts from M1.

Table 3 Panel A gives the proportion of stocks for which the forecasts generated by M2 are significantly better or worse than the forecasts produced by M1 using the Diebold-Mariano Test at the 5% significance level. Consistent with findings in the previous section, the VAR model, M2, is superior to the moving average model, M1, especially for 1- or 2-step ahead forecasts and using the MAFE as the loss function. In detail, 72.41% of ETFs experience significantly lower MAFE using M2 to predict their 1-step bid-ask spreads compared to using M1. For 2-step ahead forecasts, the proportion of ETFs with lower MAFE using M2 decreases to 56.95%.

The results of the Diebold-Mariano Test using MSFE as forecast error criteria are less dramatic. There are 29.59% of ETFs having significantly lower MSFE using M2 to predict their 1-step bid-ask spreads compared to M1. For 4-step and 5-step ahead prediction, the proportion of ETFs with higher MSFE using M2 bypasses ETFs' proportion with significantly lower MSFE using M2. This indicates that M2 becomes less efficient than M1 to predict bid-ask spreads for longer horizons.

Harvey, Leybourne, and Newbold (1997) (HLN) suggest that the D.M. test can be improved by making a bias correction to the D.M. test statistic and comparing the corrected statistic with a Student-*t* distribution with (*n-1*) degrees of freedom, rather than the standard normal. However, this test is designed only for the MSFE but not MAFE.

Table 3 Panel B shows the proportion of ETFs. The forecasts generated by M2 are significantly better or worse than those produced by M1 using the HLN test at the 5% significance level MSFE as the forecast accuracy metric. The results of the HLN test are consistent with the Mariano-Diebold Test and imply that M2 is superior to M1 for 1- or 2-step forecasts. The proportions of ETFs which record significantly lower MSFE using M2 using the HLN test are 35.71% and 19.69% for 1-step and 2-step ahead forecasts, respectively.

[Insert Table 3 about here]

4.2. Determinants of forecast errors

The effects of stock sectors and stock characteristics on the predictability of return forecasting models have been examined in literature (Phan, Sharma, and Naryan, 2015; Lawrenz and Zorn, 2017). For instance, Phan, Sharma, and Naryan (2015) find that stock return predictability based on the oil price is sector-dependent and linked to specific sector characteristics such as book-to-market ratio, dividend yield, price-earnings ratio, and trading volume. This section investigates the determinants of bid-ask spread predictability, including both ETF characteristics and market condition variables.

We use the out-of-sample forecast errors as proxies for the VAR model in predicting bid-ask spread. ETFs in the sample are categorized into seven broad sectors, including Allocation, Alternative, Commodities, Convertibles, Equity, Fixed Income, and Tax Preferred. Besides, Equity ETFs are further divided into nine sub-sectors based on their investment style following Morningstar classification. The ETF quantitative characteristics examined include ETF return volatility, ETF dollar trading volume, and ETF market value. Since these characteristics affect the ETF bid-ask spread in literature[9], they are likely to affect the forecast errors of models predicting bid-ask spread.

To assess the effect of ETF characteristics on forecast errors of the VAR model, we use the following equations:

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Allocation_{E,t} + \beta_5 Alternative_{E,t} + \beta_6 Commodities_{E,t} + \beta_7 Convertibles_{E,t} + \beta_8 Equity_{E,t} + \beta_9 FixIn_{E,t} + \epsilon_t \quad (6)$$

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Large\_Blend_{E,t} + \beta_5 Large\_Growth_{E,t} + \beta_6 Large\_Value_{E,t} + \beta_7 Mid\_Blend_{E,t} + \beta_8 Mid\_Growth_{E,t} + \beta_9 Mid\_Value_{E,t} + \beta_{10} Small\_Blend_{E,t} + \beta_{11} Small\_Growth_{E,t} + \epsilon_t \quad (7)$$

[9] See Agrrawal and Clark (2009), Rompotis (2010), Calamia, Deville, and Riva (2013).

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$, $FixIn_{E,t}$ are dummy variables accounting for different ETF broad sectors. Each dummy variable takes the value of 1 if the ETF belongs to the designated sector, and 0 otherwise. $Large\_Blend_{E,t}$, $Large\_Growth_{E,t}$, $Large\_Value_{E,t}$, $Mid\_Blend_{E,t}$, $Mid\_Growth_{E,t}$, $Mid\_Value_{E,t}$, $Small\_Blend_{E,t}$ and $Small\_Growth_{E,t}$ are dummy variables accounting for different equity styles of ETF. Each dummy variable takes the value of 1 if the ETF belongs to the designated equity style and 0 if otherwise. The reference sector in Eq. (6) is Tax Preferred and the reference style in Eq. (7) is Small Value.

The regression results of Eqs. (6) and (7) are reported in Table 4 Panel A and B. All *t*-statistics are calculated using Newey-West standard errors. In Panel A, we find that the VAR model's predictability is significantly dependent on ETF characteristics. Forecast errors measured by either *MAFE* or *Ln(MSFE)* are positively correlated with ETF return volatility, *RETVAR*, and negatively correlated with ETF market value, *LogMV*. This implies that the VAR model's predictability in forecasting ETF bid-ask spread is better for ETFs with lower return variance and larger market capitalization. The evidence of the effect of ETF dollar trading volume, *LDVOL* on the model's forecast errors, is mixed. We find that the trading activity positively correlates with *Ln(MSFE)* and negatively correlates with *MAFE*.

[Insert Table 4 about here]

Moreover, our results also suggest that the predictability of the VAR model is sector-dependent and style-dependent. The forecast errors of the model measured by either *MAFE* or *Ln(MSFE)* are largest for ETFs belonging to Commodities, Equity, and Alternative sectors, as shown in Panel A. In Panel B, the regression results using *MAFE* indicate that the VAR model predicts better the bid-ask spread of ETFs investing in large-cap stocks. When *Ln(MSFE)* is used, we find that the M2 model's forecast errors tend to be lower for large-cap than mid-cap or small-cap stocks.

Fama and French (1989) and Schwert (2002) find that their models predict stock market return is time-variant. For instance, Schwert (2002) finds that the relation between the aggregate dividend yield and future stock market return changes significantly over time. These studies imply that the predictability of a forecasting model may depend on the macro-economic environment. To account for the effect of macro-economic variables on the predictability of the VAR model in forecasting ETF bid-ask spread, we regress the following equation:

$$FOR\_ERROR_t = \alpha + \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t + \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t \quad (8)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in the federal fund rate. $TermSpread_t$ is the daily difference between the yield on a constant maturity 10-year T-bond and the federal fund rate. $DefaultSpread_t$ is the daily difference between Moody's Baa or Better Corporate Bond Index yield and the constant maturity 10-year T-bond yield. α is the constant, and ϵ_t is the error term.

In Eq. (8), the first three variables represent the stock market movement and volatility, whereas the last three variables represent interest rates' evolution. Table 5 shows the regression results of Eq. (8) with *t*-statistics computed using Newey-West standard errors. We reveal that *MAFE* and *Ln(MSFE)* from the prediction model positively correlate with market volatility measured by $WARET_t$ and negatively link to market return, $WRET_t$. The effect of market volatility proxied by $WVARRET_t$ on *MAFE* and *Ln(MSFE)* is mixed. Furthermore, we find a positive relation between forecast errors from the VAR model and $DefaultSpread_t$. In general, these results indicate that the VAR model's accuracy reduces when the market is down and volatile and when the market default risk is increasing. These results highlight the limitation of this VAR model as its accuracy deteriorates when it is most needed.

[Insert Table 5 about here]

4.3. Economic benefit of the model

This section examines the economic benefit of using the VAR model's bid-ask spread predictions to schedule trade compared to other trading schedules. We consider the perspectives of both large and retail ETF traders.

4.3.1. For large ETF trader

We test if a trading schedule derived from the model can produce economic benefits for an ETF investor with a large order to trade. Scheduling trades for large orders have significant implications for informed (Easley and O'Hara, 1987) and liquidity traders (Admati and Pfleiderer, 1988). The informed trader wants to uncover the private information from the order size to maximize gains from trade. The liquidity trader also likes to hide his demand for liquidity to avoid front running and minimize trade's implicit cost (Keim and Madhavan, 1997). Regardless of the traders' reason to trade, large traders have a strong incentive to split their orders to reduce implicit trading costs (Alam and Tkatch, 2009). As evidence, Chordia and Subrahmanyam (2011) find that while the value-weighted average monthly share turnover of stocks on NYSE increased from 5% to 26% from 1993 to 2008, the average daily number of transactions increased ninety-fold during the same period. This fact implies that splitting orders have been a norm to reduce transaction costs for many traders.

Consistent with the above literature about large traders' trading behavior, this study assumes that the investor using the VAR model to schedule his trade is a large trader who splits his order over the trading day. The trader has 13 30-minute trading horizons[10] during the trading day, and in each trading horizon, he will trade one-thirteenth of his volume scheduled for the day. His objective is to purchase ETF units at any time during each trading horizon where the bid-ask spread is lowest. For instance, at 9:30 am on 03 Jan 2011, this investor wants to trade ETF *i*. The VAR model has five forecasts of bid-ask spread from 9:35 am (1-step ahead forecast) to 9:55 am (5-step ahead forecast). If the current spread at 9:30 am is lower than all *h*-step ahead forecasts, this investor will trade immediately. Otherwise, this investor will choose the time where the bid-ask spread forecast is the lowest to trade. For example, if the 2-step ahead forecast at 9:40 am is the lowest, then an investor will trade at 9:40 am and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 am.

We compare the executed bid-ask spread using this VAR trading schedule to that of the following trading schedules:

[10] These 13 trade horizons are equivalent to 13 30-minute time intervals during the trading day.

- *TWAP trading schedule*: In this trading schedule, daily trading volume is divided equally into 13 parts. Each part is executed immediately at the beginning of each 30-minute trade horizon of the trading day. According to Cesari, Marzo, and Zagaglia (2012), TWAP is one of the main algorithmic trading rules in the stock market.
- *M.A. trading schedule*: In this trading schedule, the trader uses bid-ask spread forecasts from the moving average model to schedule his trades. The trading rules are the same as the VAR trading schedule, except we replace the bid-ask spread forecasts from the VAR model with the bid-ask spread forecasts from the moving average model.
- *Random trading schedule*: In this trading schedule, we assume that the trader can split his order more frequently than 13 times each trading day. He can trade an equal amount of his demand for each bid-ask spread quote of the trading day, and he will incur the average bid-ask spread for each trade horizon and each trading day.

This study also assumes no commission costs and opportunity costs are the same for different strategies. Furthermore, we also assume that the average premium or discount of ETFs in the sample is zero. This assumption is consistent with Hilliard's (2014) finding that the long-term premium of U.S. ETFs is not significantly different from zero. Based on these assumptions, reducing execution costs in ETF trading is determined by minimizing spread payment.

Table 6 presents the average executed bid-ask spread under different trading schedules for each time interval during the day and its corresponding economic benefit. The last row shows the pooled average of the executed bid-ask spread and economic benefit variables. We calculate the economic benefit in Table 6 as the spread discount between the executed bid-ask spread using the VAR model and under three reference trading schedules: *TWAP trading schedule, M.A. trading schedule,* and *Random trading schedule.* The formula to compute the economic benefit is:

$$ECO\_BEN_{Var,j,t}=(AVE\_BAS_{j,t} - AVE\_BAS_{Var,t})/AVE\_BAS_{j,t} \quad (9)$$

where $ECO\_BEN_{VAR,j,t}$ is the economic benefit of the VAR trading schedule compared to trading schedule j in interval t. $Ave\_BAS_{j,t}$ is the average executed bid-ask spread of ETFs using trading schedule j in interval t. $Ave\_BAS_{VAR,t}$ is the average executed bid-ask spread of ETFs using the VAR trading schedule in interval t.

From Table 6, we find that the daily average executed bid-ask spread using the VAR model to schedule trades is 36.16 basis points, which is lower than that from other models. Using the VAR model could save traders about 7.4% compared to using a TWAP trading schedule for economic benefit. The VAR trading schedule's average spread is 8.29% lower than that of the M.A. trading schedule. Compared to the average bid-ask spread of a random investor, the spread saving is as high as 30.81%. In summary, these results indicate that scheduling trades based on the VAR model's bid-ask spread forecasts can help large traders save their spread costs while allowing them to split their orders over time.

We report the intraday economic benefit patterns using the VAR model's trading schedule compared to other trading schedules in Table 6. We find that traders can enjoy economic benefits from the VAR model at any time during the trading day. For instance, the VAR trading schedule's economic benefit compared to the TWAP trading schedule, $ECO\_BEN_{VAR,\ TWAP}$, is lowest at the open and the close of the trading day. After the opening, the economic benefit rises and then becomes stable. The highest economic benefits happen during the last two intervals before the market closure.

[Insert Table 6 about here]

4.3.2. For retail ETF trader

This section compares the average bid-ask spread under different trading schedules mentioned in section 4.3.1 to a simple trading rule of trading at the close. Trading at the close has many hidden costs for traders with a large order to execute or traders possessing private information. For traders with a large order to execute, there is implementation shortfall risk as they might be able to execute only a fraction of their orders around the close. For traders possessing private information, delaying trade until the close can reduce their information advantages. Furthermore, Cushing and Madhavan (2001) also point to the risk of significant price movement at the close caused by institutional demand. Despite these disadvantages, Bacidore, Polidore, Xu, and Yang (2012) find that the closing time is generally the most actively traded day period. Some traders choose to trade around the close either because they choose the closing price as their benchmarks (e.g., index funds) or because the improved liquidity around this time attracts them. As a result, we expect that scheduling trade at the close would be enticing from the perspective of a retail ETF trader who executes only small orders and does not trade based on private information.

In table 7, we compare the average bid-ask spread under different trading schedules and the average closing bid-ask spread of ETFs. We compute the average numbers using different averaging methodologies, including pooled, cross-sectional, and time-series averages. The pooled average closing bid-ask spread of ETFs ($AVE\_BAS_{Closing}$) is only 19.69 basis points, representing a discount of 45% compared to the average bid-ask spread of the VAR trading schedule[11]. When trading at the close, the retail ETF trader described above can save up

[11] Our regression of the intraday pattern of ETF liquidity in Appendix B shows that the time-weighted bid-ask spread tends to be low during the last 15-minute interval.

significantly his spread cost compared to splitting trades over the trading day using different trading schedules.

[Insert Table 7 about here]

4.4. Economic benefit and spread volatility

In Taylor's (2002) paper, he finds that the VAR model can save trading stocks' transaction costs on the London Stock Exchange by about 34% compared to a TWAP trading schedule. We find that this spread saving for ETFs is 7.40% on average for a large ETF trader. Calculating the spread saving of the VAR trading schedule using the gap between ETF spreads throughout the day could depend on the level of spread volatility of ETF. In the extreme case that the spread is flat for the whole day, the economic benefit will be zero regardless of forecasts from the VAR model. As a result, we expect the VAR model to yield better cost savings when the spread is more volatile. In other words, we conjecture that there is more room to save spread costs by timing trades during the day when spread volatility is high.

Table 8 breaks down the daily economic benefit derived from the VAR model compared to the TWAP trading schedule ($ECO\_BEN_{Var,\ TWAP,t}$) into different spread volatility ranks and ETF sectors. In Panel A, ETFs are cross-sectionally classified into quintiles of spread volatility daily. We use two daily spread volatility measures: the daily percentage spread range (*RANSPR)* and the daily coefficient of variation of the spread (*COVARSPR*). We compute the percentage spread range by dividing the daily spread range by the daily mean bid-ask spread. The spread range is the maximum spread minus the minimum spread. We calculate the spread coefficient of variation as the ratio of the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread. Our descriptive statistics of economic benefit in Panel A show that economic benefit is higher for more spread volatile ETFs. In Panel B, we classify ETFs into various sectors. We observe higher economic benefits for ETFs like Commodities or Equity and lower economic benefit for ETFs such as Tax Preferred or Fixed Income.

[Insert Table 8 here]

To formally test our expectation, we regress the following equation:

$$ECO\_BEN_{Var,TWAP,t} = \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \quad (10)$$

where $ECO\_BEN_{VAR,\ TWAP,t}$ is the daily economic benefit of the VAR trading schedule compared to the TWAP trading schedule for each ETF. $SPR\_VOL_{E,t}$ is the daily volatility of ETF spread measured by either the daily percentage spread range ($RANSPR_{E,t}$) or the daily coefficient of variation ($COVARSPR_{E,t}$). $RETVAR_{E,t}$ is the 5-day return variance of ETF. $LDVOL_{E,t}$ is the logarithm of the daily dollar trading volume of ETF. $LogMV_{E,t}$ is the logarithm of the daily market value of ETF. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in federal fund rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the federal fund rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term.

Table 9 reports the regression results of Eq. (10). All *t*-statistics are calculated using Newey-West standard errors. We find that spread volatility positively correlates with the economic benefit calculated from the VAR model. This positive relation is also robust for both proxies of spread volatility, *RANSPR*, and *COVARSPR*. These regression results are consistent with our expectation that the more volatile the spread is, the more spread savings opportunity from the VAR model. Besides spread volatility, we also reveal other ETF characteristics that could affect the model's economic benefit. We find evidence that the economic benefit is higher for ETFs with higher return volatility (*RETVAR*), higher trading activity (*LDVOL*), and lower size (*LogMV*).

[Insert Table 9 about here]

5. Conclusion

Despite the growing importance of trading ETFs, there is little evidence of the predictability of ETF bid-ask spread. Our paper examines the degree to which investors can minimize ETF trading costs using bid-ask spread predictions from a VAR model. Using a large sample of 1,350 U.S. ETFs between January 2011 and December 2017, we find that this VAR model can produce better bid-ask spread forecasts than a moving average model in the short term. Furthermore, we document that the optimal trading schedule for ETFs to minimize bid-ask spread cost depends on traders' type. For a large ETF trader who is more likely to split his order to hide his trading motives, the VAR trading schedule is superior to other trading schedules. For a retail ETF trader who does not possess private information and trades a small amount of ETF shares, trading at the close is the best spread saving as ETF bid-ask spreads tend to be lowest around the closing time.

Finally, we reveal that the VAR trading schedule's cost-saving compared to the TWAP trading schedule is widely diverse across ETF sectors. While the benefit of timing trades is as low as 3.88% for Tax Preferred ETFs, it is nearly 9.5% for Commodities ETFs. One possible explanation for the difference in expected cost savings across ETFs and between ETF and stock could be the spread of volatility. When security is more volatile in the spread, it will have more room to minimize spread costs by timing trades. We find a positive correlation between spread volatility and spread saving, which lends support to our conjecture. Furthermore, as an ETF is a diversified portfolio where idiosyncratic risk is low and diversified, ETF has less volatility than stock. The ETFs might offer less room to minimize transaction costs than individual stocks.

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Table 1. Summary of Variables Used in the VAR Model

Panel A. By ETF Sector

ETF Sector	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I_{i,t}^{T}$
Allocation	40.03	171	2.04	0.27
Alternative	50.61	2,888	4.63	3.66
Commodities	43.94	498	3.67	0.69
Convertibles	48.89	489	2.91	0.85
Equity	45.18	634	2.76	0.83
Fixed Income	31.93	547	2.35	0.93
Tax Preferred	34.28	83	1.98	0.20
Average	43.65	988	3.00	1.31

Panel B. By Liquidity Quintiles

Liquidity Rank	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I_{i,t}^{T}$
L_1 (most liquid)	22.52	2,689	2.81	3.61
L_2	28.55	1,495	4.21	1.77
L_3	40.97	245	2.12	0.48
L_4	49.91	142	2.49	0.30
L_5 (least liquid)	77.47	50	3.25	0.12
Average	43.65	988	3.00	1.31

This table presents the descriptive statistics of variables used in the VAR model to predict the ETF bid-ask spread. $s_{i,t}$ is quoted bid-ask spread of ETF *i* measured at the end of a 5-minute time interval *t* starting from 9:35 am and ending at 4:00 pm of the trading day; $\sigma_{i,t}$ is the standard deviation of midpoint quotes during each 5-minute time interval; $V_{i,t}$ is the trading volume during each 5-minute time interval; $I_{i,t}^{T}$ is the number of trades during each 5-minute time interval. Panel A reports the average values of these variables by different ETF sectors. Panel B shows the average values for different liquidity-ranked groups with L_1 being the most liquid group and L_5 the least liquid group.

Table 2. Assessing Forecast Quality Using MAFE and MSFE

Panel A. ETFs with Better h-Step Forecast Using the VAR-Model

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Number of ETFs have lower MAFE using M2 than M1	1,060	949	726	526	375
Percentage of ETFs have lower MAFE using M2 than M1	78.55%	70.29%	53.85%	38.96%	27.81%
Number of ETFs have lower MSFE using M2 than M1	732	488	301	195	145
Percentage of ETFs have lower MSFE using M2 than M1	54.20%	36.13%	22.30%	14.47%	10.73%
Total number of ETFs	1,350	1,350	1,350	1,350	1,350

Panel B. Average Values of MAFE and MSFE for M1 and M2

		h: the number of periods ahead forecast				
		1	*2*	*3*	*4*	*5*
Average value of MAFE	M1	0.00258	0.00256	0.00256	0.00256	0.00256
	M2	0.00145	0.00260	0.02344	0.81151	37.54006
Average value of MSFE	M1	0.00017	0.00017	0.00017	0.00017	0.00017
	M2	0.00222	0.64134	1.1172	2.1895	4.6879

This table presents the statistics of mean absolute forecast error (MAFE) and mean squared forecast error (MSFE) of the VAR model (M2) and a moving average model (M1) to predict ETF bid-ask spread. Panel A shows the number and the percentage of ETFs having lower MAFE or MSFE using M2 compared to M1. Panel B shows the average values of MAFE and MSFE for M1 and M2.

Table 3. Comparing Forecast Quality

Panel A. Using Diebold-Mariano Test (1995)

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Proportion of ETFs have significantly *lower* MAFE using M2 than M1	72.41%	56.95%	38.53%	25.55%	16.73%
Proportion of ETFs have significantly *higher* MAFE using M2 than M1	0.71%	0.99%	5.08%	10.16%	15.46%
Proportion of ETFs have significantly *lower* MSFE using M2 than M1	29.59%	15.07%	7.42%	4.29%	2.73%
Proportion of ETFs have significantly *higher* MSFE using M2 than M1	1.09%	2.58%	7.73%	12.41%	15.93%

Panel B. Using HLN (1997) Test

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Proportion of ETFs have significantly *lower* MSFE using M2 than M1	35.71%	19.69%	10.23%	6.07%	4.30%
Proportion of ETFs have significantly *higher* MSFE using M2 than M1	1.91%	3.39%	5.01%	6.14%	6.92%

This table presents the results of the prediction accuracy test for the MAFE and MSFE derived from the VAR model (M2), and a moving average model (M1) to predict ETF bid-ask spread. Panel A reports the percentage of ETFs which have significantly lower (higher) MAFE or MSFE using M2 compared to using M1 indicated by Mariano-Diebold (1995) test. Panel B reports the percentage of ETFs that have significantly lower (higher) MSFE using M2 compared to using M1 indicated by Harvey, Leybourne, and Newbold (HLN) (1997) test.

Table 4. Effect of ETF Characteristics on Forecast Errors

Panel A. Effect by ETF sector	MAFE	Ln(MSFE)	*Panel B. Effect by ETF equity style*	MAFE	Ln(MSFE)
RETVAR	0.029***	34.3***	RETVAR	0.063***	71.12***
	(19.44)	(128.7)		(27.69)	(135.97)
LDVOL	-0.122*	0.052***	LDVOL	0.158**	0.057***
	(-1.74)	(42.99)		(2.33)	(36.63)
LogMV	-0.842***	-0.21***	LogMV	-0.361***	-0.12***
	(-6.63)	(-95.01)		(-3.00)	(-44.55)
Allocation	2.502	0.627***	Large_Blend	2.454***	-0.257***
	(1.55)	(22.18)		(2.95)	(-13.44)
Alternative	6.361***	0.699***	Large_Growth	3.314***	-0.048***
	(4.63)	(29.08)		(3.73)	(-2.37)
Commodities	12.4***	1.390***	Large_Value	1.983**	-0.075***
	(6.50)	(41.69)		(2.34)	(-3.84)
Convertibles	12.9	1.776***	Mid_Blend	4.191***	0.358***
	(1.57)	(12.36)		(4.61)	(17.12)
Equity	7.236***	1.203***	Mid_Growth	3.166***	0.115***
	(5.57)	(52.93)		(3.13)	(4.96)
FixIn	2.141	0.218***	Mid_Value	2.138**	0.143***
	(1.60)	(9.32)		(2.30)	(6.7)
Intercept	17.6***	-13.7***	Small_Blend	2.634**	0.039*
	(10.70)	(-476)		(2.51)	(1.63)
			Small_Growth	3.542**	-0.015
				(2.57)	(-0.47)
			Intercept	9.902***	-13.9***
				(7.88)	(-480)
N Obs.	806,242	806,242	N Obs.	483,519	483,519
Adj. R^2	0.0012	0.0742	Adj. R^2	0.0018	0.0554

Table 4 Panel A presents the regression results of the following model:

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Allocation_{E,t} + \beta_5 Alternative_{E,t} + \beta_6 Commodities_{E,t} + \beta_7 Convertibles_{E,t} + \beta_8 Equity_{E,t} + \beta_9 FixIn_{E,t} + \epsilon_t \quad (6)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$, $FixIn_{E,t}$ are dummy variables accounting for different ETF sectors. Each dummy variable takes the value of 1 if ETF belongs to the designated sector and 0 otherwise. The reference sector is Tax Preferred.

Table 4 Panel B presents the regression results of the following model:

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Large\_Blend_{E,t} + \beta_5 Large\_Growth_{E,t} + \beta_6 Large\_Value_{E,t} + \beta_7 Mid\_Blend_{E,t} + \beta_8 Mid\_Growth_{E,t} + \beta_9 Mid\_Value_{E,t} + \beta_{10} Small\_Blend_{E,t} + \beta_{11} Small\_Growth_{E,t} + \epsilon_t \quad (7)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Large\_Blend_{E,t}$, $Large\_Growth_{E,t}$, $Large\_Value_{E,t}$, $Mid\_Blend_{E,t}$, $Mid\_Growth_{E,t}$, $Mid\_Value_{E,t}$, $Small\_Blend_{E,t}$ and $Small\_Growth_{E,t}$ are dummy variables accounting for different equity styles of ETF. Each dummy variable takes the value of 1 if ETF belongs to the designated equity style and 0 otherwise. The reference style is Small Value. All *t*-statistics are calculated using Newey-West standard errors. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Table 5. Effect of Macro-Variables on Forecast Errors

Independent Variables	Using MAFE			Using Ln(MSFE)		
	(1)	(2)	(3)	(4)	(5)	(6)
WRET	-0.589***	-0.577***	-0.589***	-7.120***	-6.89***	-7.115***
	(-2.55)	(-2.51)	(-2.55)	(-17.32)	(-19.28)	(-17.31)
WARET	5.859***	4.886***	5.861***	109.92***	84.25***	109.81***
	(6.68)	(5.50)	(6.68)	(70.4)	(61.11)	(70.33)
WVARRET	0.752***	0.788***	0.753***	-339.8***	-29.34***	-339.2***
	(2.93)	(3.07)	(2.94)	(-7.45)	(-74)	(-7.43)
ShortRate	-0.08	-0.062	-0.079	-0.775***	-0.427***	-0.774***
	(-1.08)	(-0.84)	(-1.08)	(-5.88)	(-3.73)	(-5.87)
TermSpread	-0.006	-0.002	-0.006	0.115	0.173**	0.116
	(-0.15)	(-0.05)	(-0.15)	(1.55)	(2.67)	(1.55)
DefaultSpread	0.218***	0.212***	0.218***	0.148***	1.456***	1.664***
	(2.62)	(2.57)	(2.62)	(11.11)	(11.33)	(11.12)
Intercept	0.118***			-14.73***		
	(30.17)			(212)		
ETF FEs	No	Yes	No	No	Yes	No
Year F.E.s	No	No	Yes	No	No	Yes
N Obs.	810,087	810,087	810,087	810,087	810,087	810,087
Adj. R^2	0.004	0.004	0.004	0.0189	0.0259	0.0190

This table presents the results of the following model:

$$FOR\_ERROR_t = \alpha + \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t + \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t \quad (8)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in federal fund rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the federal fund rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term. All *t*-statistics are calculated using Newey-West standard errors. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Table 6. Economic Benefit of VAR Model to Trade ETFs

Time Interval	Average Bid-Ask Spread (in basis points)				Economic Benefit		
	AVE_BAS_{VAR}	AVE_BAS_{TWAP}	AVE_BAS_{MA}	AVE_BAS_{Random}	$ECO\_BEN_{VAR,TWAP}$	$ECO\_BEN_{VAR,MA}$	$ECO\_BEN_{VAR,Random}$
1	38.56	40.27	40.68	65.52	4.25%	5.21%	41.15%
2	32.35	34.19	36.01	46.71	5.38%	10.16%	30.74%
3	31.24	32.79	34.60	41.92	4.73%	9.71%	25.48%
4	30.54	32.02	33.82	41.08	4.62%	9.70%	25.66%
5	30.21	31.46	33.48	41.03	3.97%	9.77%	26.37%
6	30.15	31.44	33.32	41.74	4.10%	9.51%	27.77%
7	29.78	31.05	33.44	40.18	4.09%	10.94%	25.88%
8	30.09	32.29	33.61	39.72	6.81%	10.47%	24.24%
9	29.99	31.19	33.46	40.24	3.85%	10.37%	25.47%
10	29.62	30.90	33.12	40.65	4.14%	10.57%	27.13%
11	29.00	31.29	35.01	39.99	7.32%	17.17%	27.48%
12	132.4	147.4	88.97	140.1	10.18%	-48.81%	5.50%
13	91.69	94.18	107.82	56.01	2.64%	14.96%	-63.70%
Mean	36.16	39.05	39.43	52.27	7.40%	8.29%	30.81%

This table presents the executed bid-ask spread under different trading schedules for a large ETF trader. These trading schedules are:

- *VAR trading schedule*: The trader has 13 30-minute trading horizons during the trading day, and in each trading horizon, he will trade one-thirteenth of his volume scheduled for the day. His objective is to purchase ETF units at any time during each trading horizon where the bid-ask spread is lowest. For instance, at 9:30 am on 03 Jan 2011, this investor wants to trade ETF *i*. Based on the VAR-model, he has 5 forecasts of bid-ask spread at 9:35am (1-step ahead forecast) to 9:55 am (5-step ahead forecast). If the current spread around 9:30 am is lower than all *h*-step ahead forecasts, this investor will trade immediately. Otherwise, this investor will choose the point in time where the bid-ask spread forecast is lowest to trade. For example, if the 2-step ahead forecast at 9:40 am is lowest then the investor will trade at 9:40 am and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 am.
- *TWAP trading schedule*: In this trading schedule, trades take place immediately during the 30-minute trade horizon. In the above example, the bid-ask spread at around 9:30 am is the bid-ask spread executed by investors.
- *M.A. trading schedule*: In this trading schedule, the trader uses bid-ask spread forecasts from the moving average model to schedule his trades. The trading rules are the same as the VAR trading schedule except that the bid-ask spread forecasts from the VAR model are replaced by bid-ask spread forecasts from the moving average model.

- *Random trading schedule*: In this trading schedule, we assume that the trader can split his order more frequently than 13 times each trading day. He can trade an equal amount of his order for each bid-ask spread quote of the trading day and he will incur the average bid-ask spread for each trade horizon and each trading day.

The economic benefit in Table 6 is calculated as the spread discount between the executed bid-ask spread using the VAR model and that under three reference trading schedules: *TWAP trading schedule, M.A. trading schedule,* and *Random trading schedule.* The formula to compute the economic benefit is:

$$ECO\_BEN_{VAR,j,t}=(AVE\_BAS_{j,t} - AVE\_BAS_{Var,t})/AVE\_BAS_{j,t} \quad (9)$$

where $ECO\_BEN_{VAR,j,t}$ is the economic benefit of the VAR trading schedule compared to trading schedule j in interval t. $AVE\_BAS_{j,t}$ is the average executed bid-ask spread of ETFs using trading schedule j in interval t. $AVE\_BAS_{VAR,t}$ is the average executed bid-ask spread of ETFs using the VAR trading schedule in interval t.

Table 7. Average Bid-Ask Spreads of Different Trading Schedules

Variables	Pooled Average	Cross-sectional Average	Time-series Average
AVE_BAS_{VAR}	36.16	37.67	38.90
AVE_BAS_{TWAP}	39.05	41.07	42.42
AVE_BAS_{MA}	39.43	40.04	40.33
AVE_BAS_{Random}	52.77	50.32	53.99
AVE_BAS_{Close}	19.69	15.82	21.95

This table presents the daily average executed bid-ask spread under different trading schedules. The average bid-ask spread of each model is calculated using three following calculation methodologies: *1/Pooled average*: Averaging all executed bid-ask spread of each trading rules for all ETFs in the sample; *2/ Cross-sectional average*: First daily executed bid-ask spread is calculated for each ETFs as the average of all executed bid-ask spreads during the day (for VAR, TWAP, and M.A. trading rules). For trading at the close strategy, a daily executed bid-ask spread is the closing bid-ask spread. For random trading strategy, a daily executed bid-ask spread is the average of all bid-ask spreads during the day. Daily executed bid-ask spreads are averaged for each ETF over the sample period then the results are averaged cross-sectionally across all ETFs to have the average bid-ask spread for each trading rule and *3/ Time-series average*: Daily executed bid-ask spread for each ETF is calculated the same as the cross-sectional average. The daily executed bid-ask spreads for ETFs in the sample are averaged for each day and then the results are averaged across the research period to have the average bid-ask spread for each trading rule.

Table 8. Breakdown of Economic Benefit

Panel A. By Spread Volatility

ETF Spread Volatility Ranking	$ECO\_BEN_{VAR,TWAP}$	
	Ranked by RANSPR	Ranked by COVARSPR
1 (*Lowest spread volatility*)	4.47%	4.76%
2	5.29%	5.29%
3	5.91%	5.77%
4	6.59%	6.41%
5 (*Highest spread volatility*)	7.17%	7.21%

Panel B. By ETF Sector

ETF Sector	Number of ETFs	$ECO\_BEN_{VAR,TWAP}$
Allocation	30	4.67%
Alternative	271	6.46%
Commodities	25	9.47%
Convertibles	2	9.64%
Equity	796	6.01%
Fixed Income	199	5.03%
Tax Preferred	27	3.88%

This table presents the economic benefit of the VAR trading schedule compared to the TWAP trading schedule ($ECO\_BEN_{VAR,TWAP}$) of different ETF groups classified by their spread volatilities (Panel A) and sectors (Panel B). In Panel A, we use two measures of daily spread volatility, which are the daily percentage spread range (*RANSPR)* and the daily coefficient of variation of the spread (*COVARSPR*). *RANSPR* is computed by dividing the daily spread range to the daily mean bid-ask spread. Spread range is the maximum spread minus the minimum spread. *COVARSPR* is calculated by dividing the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread.

Table 9. Economic Benefit and Spread Volatility

Independent Variables	Using Spread Range as Proxy for Spread Volatility			Using Coefficient of Variation as Proxy for Spread Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
RANSPR	0.014***	0.017***	0.014***			
	(29.44)	(31.89)	(29.45)			
COVARSPR				1.022***	1.014***	1.01***
				(70.70)	(68.41)	(69.84)
RETVAR	39.83***	34.05***	39.81***	45.85***	0.445***	0.644***
	(18.96)	(10.52)	(18.95)	(21.89)	(9.29)	(24.91)
LDVOL	0.010***	0.089***	0.047***	0.049***	0.098***	0.059***
	(4.69)	(7.67)	(4.70)	(4.97)	(8.46)	(6.00)
LogMV	-0.485***	-0.803***	-0.485***	-0.589***	-0.844***	-0.571***
	(-26.86)	(-28.37)	(-26.85)	(-32.56)	(-29.85)	(-31.53)
WRET	-15.01***	-14.67***	-15.01***	-16.78***	-16.71***	-16.62***
	(-4.54)	(-4.47)	(-4.53)	(-5.08)	(-5.11)	(-5.04)
WARET	124.99***	111.3***	124.9***	124.87***	114.7***	99.39***
	(9.83)	(8.53)	(9.82)	(9.85)	(8.47)	(7.76)
WVARRET	-865.28**	-747.9**	-866.2**	-867.3**	-335.8	-144.2
	(-2.35)	(-2.03)	(-2.35)	(-2.36)	(-0.92)	(-0.39)
ShortRate	0.876	1.268	0.877	1.689	1.880*	1.67
	(0.86)	(1.2)	(0.82)	(1.59)	(1.78)	(1.57)

TermSpread	0.489	0.607	0.49	0.634	0.712	0.616
	(0.41)	(1.02)	(0.82)	(1.06)	(1.20)	(1.03)
DefaultSpread	4.657***	4.402***	4.669***	4.367***	4.274***	4.431***
	(3.91)	(3.73)	(3.92)	(3.67)	(3.63)	(3.73)
Intercept	6.58***			6.634***		
	(40.65)			(41.15)		
ETF FEs	No	Yes	No	No	Yes	No
Year F.E.s	No	No	Yes	No	No	Yes
N Obs.	829,507	829,507	829,507	829,507	829,507	829,507
Adj. R^2	0.0038	0.0242	0.0038	0.0089	0.0285	0.0091

This table presents the regression results of the following model:

$$ECO\_BEN_{VAR,TWAP,E,t} = \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \quad (10)$$

where $ECO\_BEN_{VAR,TWAP,E,t}$ is the daily economic benefit of the VAR trading schedule compared to TWAP trading schedule for each ETF. $SPR\_VOL_{E,t}$ is the daily volatility of ETF spread measured by either daily percentage spread range ($RANSPR_{E,t}$) or the daily coefficient of variation of the spread ($COVARSPR_{E,t}$). The percentage spread range is computed by dividing the daily spread range to the daily mean bid-ask spread. Spread range is the maximum spread minus the minimum spread. The coefficient of variation is calculated by dividing the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of daily dollar trading volume of ETF; $LogMV_{E,t}$ is the daily logarithm of the market value of ETF. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in federal fund rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the federal fund rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term. All *t*-statistics are calculated using Newey-West standard errors. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Appendix A. Time-Weighted Bid-Ask Spread and Dollar Volume-Weighted Effective Spread

Panel A. By Year

Year	Number of ETFs	BAS (in bps)	ESpread (in bps)
2011	402	44.04	24.41
2012	466	45.61	24.40
2013	551	40.04	20.43
2014	629	37.11	20.78
2015	827	43.87	26.33
2016	941	48.71	26.57
2017	1,245	37.48	20.26

Panel B. By ETF Sector

ETF Sector	Number of ETFs	BAS (in bps)	ESpread (in bps)
Allocation	30	46.49	24.12
Alternative	271	44.11	27.59
Commodities	25	49.28	26.11
Convertibles	2	141.67	72.36
Equity	796	41.72	22.76
Fixed Income	199	40.13	20.00
Tax Preferred	27	43.41	21.40

This table presents the values of time-weighted bid-ask spread (*BAS*) and dollar volume-weighted effective spread (*ESpread*) of ETF in the sample. These figures are calculated every 15 minutes and averaged for daily and yearly calculation. In Panel A, the spreads are reported yearly over the research period. In Panel B, the spreads are presented according to seven ETF sectors classified by Morningstar.

Appendix B. Intraday Patterns of ETF Liquidity

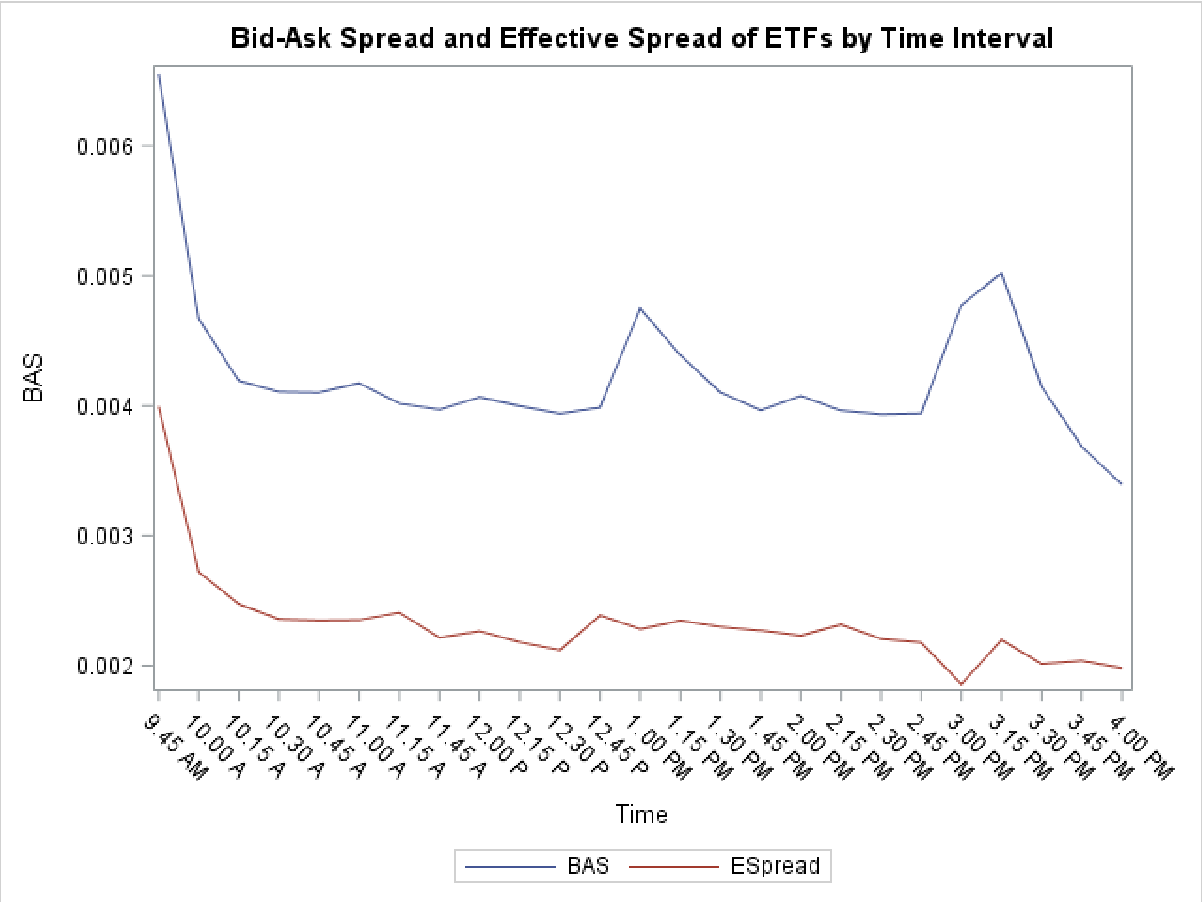
Independent Variables	BAS (1)	ESpread (2)
D_1	24***	17.6***
	(18.12)	(10.17)
D_2	5.2***	4.82***
	(4.78)	(5.13)
D_3	0.39	2.36***
	(0.51)	(2.84)
D_4	-0.4	1.17***
	(-0.57)	(2.33)
D_{25}	-4.6***	-2.0***
	(-9.84)	(-3.20)
D_{26}	-7.6***	-2.6***
	(-16.81)	(-6.18)
Exchange_Dummy	2.21***	1.9***
	(4.70)	(6.77)
Intercept	41.13***	22.05***
	(205.4)	(143.6)

This table reports the regression results of the following equation:

$$S_{i,j,d} = \alpha + \sum_{j=1}^{4} \beta_j D_j + \sum_{j=25}^{26} \beta_j D_j + Exch\_Dummy_i + \varepsilon_{i,i,d} \quad (11)$$

where $S_{i,j,d}$ is the spread of ETF i during interval j of day d with spread can be either time-weighted bid-ask spread or dollar volume-weighted effective spread and D_j is the dummy variable for time interval j. D_j has a value of 1 if it is the jth interval and 0 otherwise. Each trading day is divided into 26 15-minute time intervals. $Exch\_Dummy_i$ has a value of 1 if ETF i listed on NASDAQ and 0 if listed on NYSE. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Appendix C. Figure of Intraday Pattern of ETFs Liquidity



This figure shows the intraday pattern of time-weighted bid-ask spread (*BAS*: the blue line) and dollar volume-weighted effective spread (*ESpread*: the red line) of 1,350 ETFs over the period between 2011 and 2017. The trading time starts from 9:30 am to 4:00 pm and is divided into 26 15-minute time intervals.