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Predicting ETF liquidity

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Abstract
Substantial transaction costs are incurred in exchange-traded fund (ETF) trading each year. This article examines a vector autoregressive (VAR) model's performance and other trading schedules to time trades in a large sample of 1350 ETFs over the 2011–2017 period. We reject the notion of a one-size-fits-all trading schedule that maximizes spread savings for all ETF traders. ETF traders who want to split their orders could save 7.40% of ETF spread costs, whereas trading at the market closing time would be optimal for ETF traders without motives to split trades. The spread savings for ETF traders are diverse across ETF sectors and depend on the spread volatility.

JEL Classification: G11, G23

Keywords
Bid-ask spread, diversification, ETFs, forecasting, liquidity, portfolio liquidity

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 (e.g. Groß-KlußMann and Hautsch, 2013; Taylor, 2002; Wald and Horrigan, 2005). We contribute to the literature by considering the extent to which traders can minimize transaction costs in trading

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exchange-traded funds (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 the New York Stock Exchange, as of March 2020, ETFs accounted for approximately 30% of all US equity trading by value.[1] The average daily transaction value of US ETFs was US$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 (e.g. Ben-David et al., 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 et al. (2020) find that an ETF with greater market liquidity tends to charge higher 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 US ETFs are around US$15 billion in 2020, whereas their daily trading volume is about US$150 billion.[4] Given the above reasons, reducing transaction costs is a crucial topic for ETF investors.

Besides the above reasons, predicting ETF bid-ask spreads has meaningful implications for ETF authorized participants (APs) in conducting ETF arbitrage activities. According to Bae and Kim (2020), the lack of liquidity in ETF would lead to mispricing problems of ETF net asset value (NAV) or index returns as arbitrage activities must occur simultaneously on both ETF and underlying asset markets. If ETF liquidity is expected to be low, APs would wait for a tracking error to widen or increase the bid-ask spread to meet their required return on arbitrage.

In this article, 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 1350 non-leveraged US ETFs between January 2011 and December 2017. Our VAR model assumes 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), Calamia et al. (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 bring meaningful transaction cost savings for 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 Diebold and Mariano's (1995) test and Harvey et al.'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 macroeconomic conditions. The ETF characteristics, sector and style affect the spread forecast accuracy. Forecast errors are broader when an ETF is more 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 macroeconomic conditions in certain periods (Fama and French, 1989; Schwert, 2002). Using a set of macroeconomic 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 ETF traders who use its bid-ask spread predictions to time their trades. The average executed bid-ask spread of hypothetical ETF traders using bid-ask spread forecasts from the VAR model to schedule their trades is compared to that using other trading schedules. For ETF traders who want to hide their 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 ETF traders 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 ETF traders who do not need to split their orders. ETFs' average closing bid-ask spread is 45% lower than the average executed bid-ask spread 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 cancelled out, and 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 such as 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 on ETF liquidity. First, to the best of our knowledge, our present work is the first to predict ETF liquidity. On the one hand, compared to individual stocks, ETFs provide lower trading costs and have lower adverse selection costs (e.g. Chelley-Steeley and Park, 2010; Hegde and McDermott, 2004). As adverse selection costs contribute substantially to bid-ask spread fluctuations (Foster and Viswanathan, 1993), by having a lower proportion of adverse selection costs, ETF liquidity would be more predictable than stock liquidity. On the other hand, compared to stocks, creation/redemption activities are another determinant of the ETF bid-ask spread, introducing new uncertainty to predicting ETF liquidity (Ackert and Tian, 2008; Atanasova and Weisskopf, 2020). Therefore, by investigating the predictability of ETFs, our article contributes to the literature by shedding more light on the question of whether ETF or stock liquidity is more predictable. Our empirical results indicate that ETF liquidity is less predictable than stock liquidity using the VAR model, supporting the idea that creation/redemption activities are a crucial determinant of the ETF bid-ask spread and thus should be used for developing more efficient ETF liquidity prediction models.

Second, our research examines the degree to reduce the ETF transaction costs using ETF bid-ask spread predictions. We find the VAR model helps ETF traders who split their orders save their spread costs compared to other trading schedules. However, for ETF traders without motives to split their trades, it is optimal to trade at the close to minimize spread costs. The benefit of splitting and timing trades using the VAR trading schedule compared to using the TWAP trading schedule tends to be lower for less volatile ETF sectors such as 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 such as 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 the limitations of this prediction model. When liquidity has a great chance of drying up in the market, predictions of ETF intraday liquidity using the VAR model are less reliable.

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

The remainder of the article is structured as follows. Section 2 reviews related literature. Section 3 presents the data and methodologies used in this article. 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

2.1. Differences between ETF and stock liquidity

Extant literature on ETF suggests that ETF liquidity differs from stock liquidity in at least two critical aspects, and in turn, these differences would affect their predictability. The first difference is that ETFs possess two layers of liquidity, whereas stocks have only one (Henderson and Buetow, 2014). Both ETFs and stocks are traded on exchanges, and their bid-ask spreads (i.e. liquidity) are observable. The observed bid-ask spreads of ETFs constitute the first layer of liquidity. However, unlike stocks, ETFs have a second layer of liquidity through the creation/redemption mechanism. When there is an imbalance in the supply and demand of an ETF in the secondary market, APs of the ETF can create or redeem ETF share units with the ETF sponsor by buying or receiving ETF underlying stocks. For instance, when ETF shares are in demand on the secondary market, APs can buy the underlying stocks of the ETF and exchange them for the ETF sponsor to receive new ETF unit shares. Then they can sell ETF unit shares on the secondary market to meet the market demand. More importantly, the literature indicates that there is an association between the first and second layers of ETF liquidity. Ackert and Tian (2008) find that US ETFs with lower mispricing (i.e. more efficient creation/redemption mechanism) tend to have lower bid-ask spreads. In an international context, Atanasova and Weisskopf (2020) document that international ETFs are more liquid when they exhibit a lower absolute value of ETF premium/discount. Since ETF creation/redemption activities constitute another driver of the ETF bid-ask spread, predicting ETF liquidity (i.e. bid-ask spread) would be more difficult than predicting stock liquidity.

Besides this crucial difference, theoretical market microstructure models predict that ETFs should be more liquid than underlying stocks (e.g. Gorton and Pennacchi, 1993; Subrahmanyam, 1991). This theoretical prediction is built upon the established literature about the decomposition of bid-ask spread (e.g. Glosten and Milgrom, 1985; Ho and Stoll, 1981; Stoll, 1978, 1989; among others). Stoll (1978, 1989) posits that the costs of market makers fall into three categories: order-processing costs, inventory-holding costs and adverse selection costs. Ho and Stoll (1981) emphasize the role of inventory-holding costs in determining bid-ask spread by modelling the optimal bid-ask spread as a function of dealer's desired level of inventory. Meanwhile, according to the seminal work of Glosten and

Milgrom (1985), the bid-ask spread of a stock includes an adverse selection cost component to compensate market dealers for taking the risk of trading with informed traders. They document that the presence of traders with superior information (i.e. insiders) leads to a positive bid-ask spread even when the dealer is risk-neutral and makes zero expected profits. Therefore, as a portfolio is more diversified by holding many securities, Subrahmanyam (1991) argues that a portfolio should have less asymmetric information than an individual stock. As such, he predicts that a tradable stock basket (i.e. an ETF) should be more liquid than its underlying stocks due to the lower adverse selection cost component. Most subsequent studies on ETF find empirical results which are consistent with this prediction. Hegde and McDermott (2004) compare the bid-ask spreads and their components of two ETFs, namely the DIAMONDS (tracking Dow Jones Industrial Average) and the Q's (tracking NASDAQ 100 Index), with those of the corresponding underlying stock baskets. They find that the ETFs are more liquid than their underlying stock portfolio because they exhibit lower adverse selection costs. Marshall et al. (2018) and Broman and Shum (2018) also find similar results regarding the magnitude difference between ETF liquidity and stock liquidity. As adverse selection costs are considered the most important contributor to intraday and interday spread fluctuation (Foster and Viswanathan, 1993), the lower proportion of adverse selection costs of ETFs implies that ETF bid-ask spreads are less volatile than those of stocks and therefore, more predictable.

In summary, the aforementioned differences between ETF and stock liquidity provide mixed answers on whether ETF liquidity or stock liquidity is more predictable. On the one hand, creation/redemption activities might cause ETF bid-ask spreads more uncertain compared to stocks. On the other hand, lower adverse selection costs might reduce noises in ETF bid-ask spread fluctuations, making ETF liquidity more predictable.

2.2. Predicting liquidity models

While the 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 et al. (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 cost 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' (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 the 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 four US mid-cap stocks and find that the predictions from their model can help traders save 8.4%–10.9% of spread costs.

Variables used to predict stock bid-ask spread in Taylor's (2002) model are well-known in the 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 (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 et al. (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 the 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. Calamia et al. (2013) reveal that the 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 would be useful to predict ETF liquidity.

3. Data and methodologies

3.1. Data

We conduct our research using intraday data from 1350 US ETFs during the period between 2011 and 2017. First, we obtain data on all ETFs from the Center of Research in Security Prices (CRSP) stock database identified by their share code of 73. Leveraged ETFs are excluded from the sample as they exhibit specific trading characteristics (e.g., Ivanov and Lenkey, 2018; Shum et al., 2016). 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 a.m. and 4:00 p.m.

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 price 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 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 1350 ETFs from 1 January 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 a.m. and ending at 4:00 p.m. 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 model (2002), we impose a lag length equal to one trading day in the model, and the remaining lag order is estimated using the Akaike information criterion (AIC). This specification accounts for periodic components in the variables. As a trading day can be divided into 78 5-minute intervals, we use a lag order of 78 in our VAR model. Descriptive statistics of ETF quoted bid-ask spread and effective spread and the evidence of their periodicities can be found in Appendices 1 and 2, respectively. Appendix 3 plots the intraday patterns of ETF quoted bid-ask spread and effective spread. Upon completion of each estimation of the model, the model forecasts the liquidity at 1-step ahead (5 minutes ahead), 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 equation (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 a.m. on 3 January 2011 and ends at 4:00 p.m. on 29 December 2017. Each day has 390 minutes of trading time, which equals 78 5-minute time intervals. The first in-sample data used starts at 9:35 a.m. on 3 January 2011 and ends at 4:00 p.m. on 7 January 2011. Estimating equation (1) using this sample data will generate bid-ask spread forecasts for 9:35 a.m., 9:40 a.m., 9:45 a.m., 9:50 a.m. and 9:55 a.m. on 10 January 2011. The second in-sample data starts at 10:05 a.m. on 3 January 2011 and ends at 10:00 a.m. on 10 January 2011. Thus, the in-sample data is rolled over every 30 minutes with a fixed estimation window of five trading days.

4. Empirical results

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

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 spread follows a random walk while the spread itself is a white noise process with positive mean'. Therefore, this model 'generates forecasts equal to the mean of the in-sample period spread' (Taylor, 2002: 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

Table 1. Summary of variables used in the VAR model.

ETF sector	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I^T_{i,t}$
Panel A. By ETF sector				
Allocation	40.03	171	2.04	0.27
Alternative	50.61	2888	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
Liquidity rank	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I^T_{i,t}$
Panel B. By liquidity quintiles				
L_1 (most liquid)	22.52	2689	2.81	3.61
L_2	28.55	1495	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 the quoted bid-ask spread of ETF *i* measured at the end of a 5-minute time interval *t* starting from 9:35 a.m. and ending at 4:00 p.m. 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; and $I^T_{i,t}$ 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. VAR: vector autoregressive; ETF: exchange-traded fund.

$$MAFE = \frac{1}{T}.\sum_{t=1}^{T}\left|y_{t+h} - y'_{t+h}\right| \tag{2}$$

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

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 time $(t+h)$.

Table 2 presents a summary of the comparison between the 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)

Table 2. Assessing forecast quality using MAFE and MSFE.

	h: the number of periods ahead forecast				
	1	2	3	4	5
Panel A. ETFs with better h-step forecast using the VAR-model					
Number of ETFs have lower MAFE using M2 than M1	1060	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	1350	1350	1350	1350	1350

h: the number of periods ahead forecast	Variable	Mean	SD	10th Pctl.	90th Pctl.	Kurtosis	Skewness
Panel B. Summary statistics of MAFE and MSFE for M1 and M2							
1	$MAFE_{M2}$	0.00145	0.04648	0.000042	0.002107	34.46	31.81
	$MAFE_{M1}$	0.00258	0.01351	0.000085	0.004935	10.20	5.10
	$MSFE_{M2}$	0.00222	0.91141	0.000000002	0.000004	89.68	58.88
	$MSFE_{M1}$	0.00017	0.00589	0.000000007	0.000024	95.96	47.98
2	$MAFE_{M2}$	0.00260	0.80639	0.000057	0.002781	46.00	39.08
	$MAFE_{M1}$	0.00256	0.01347	0.000085	0.004907	10.33	5.17
	$MSFE_{M2}$	0.64134	1.39531	0.000000003	0.000007	90.19	59.10
	$MSFE_{M1}$	0.00017	0.00590	0.000000007	0.000024	98.74	49.37
3	$MAFE_{M2}$	0.02344	2.12152	0.000065	0.003279	71.14	50.57
	$MAFE_{M1}$	0.00256	0.01349	0.000085	0.004903	10.23	5.11
	$MSFE_{M2}$	1.1172	3.28913	0.000000004	0.000011	96.68	62.01
	$MSFE_{M1}$	0.00017	0.00588	0.000000007	0.000024	96.32	48.16
4	$MAFE_{M2}$	0.81151	14.3232	0.000069	0.003656	84.17	56.33
	$MAFE_{M1}$	0.00256	0.01342	0.0000845	0.004896	10.27	5.13
	$MSFE_{M2}$	2.1895	32.2135	0.000000005	0.000013	97.69	62.48
	$MSFE_{M1}$	0.00017	0.00584	0.000000007	0.000024	98.68	49.34
5	$MAFE_{M2}$	3.754006	6.95012	0.000073	0.003963	81.56	55.27
	$MAFE_{M1}$	0.00256	0.01349	0.000085	0.004894	10.28	5.14
	$MSFE_{M2}$	46.879	124.212	0.000000005	0.000015	97.43	62.36
	$MSFE_{M1}$	0.00017	0.00591	0.000000007	0.000024	96.95	48.48

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 descriptive statistics including mean and standard deviation (SD), 10th and 90th percentiles (Pctl.), kurtosis and skewness of MAFE and MSFE for M1 and M2.
ETF: exchange-traded fund; VAR: vector autoregressive.

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 two-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 descriptive statistics of MAFE and MSFE for M1 and M2. Overall, the average values of MAFE 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. However, the mean values of MSFE for M2 are substantially higher than for M1 for all h-step forecast ahead. The standard deviation column shows that the MAFE and MSFE of M2 are more volatile than those of M1. In addition, the leptokurtic distribution (e.g. kurtosis greater than 3) of MAFE and MSFE indicates that both M1 and M2 are subject to a high possibility of extremely low and high values of forecast errors. Finally, both forecast error measures of M1 and M2 exhibit positive skewness, suggesting extremely positive forecast errors are common.

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

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

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

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 DM is the Diebold–Mariano statistic. We use the DM statistic 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 and 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 and 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 predictions, 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 et al. (1997) (Harvey, Leybourne and Newbold (HLN)) suggest that the Diebold and Mariano test can be improved by making a bias correction to the DM 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 for 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 Diebold and Mariano test and imply that M2 is superior to M1 for 1- or 2-step forecasts. The proportions of ETFs that record significantly lower MSFE using M2 with the HLN test are 35.71% and 19.69% for 1-step and 2-step ahead forecasts, respectively.

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 the literature (Lawrenz and Zorn, 2017; Phan et al., 2015). For

Table 3. Comparing forecast quality.

	h: the number of periods ahead forecast				
	1	2	3	4	5
Panel A. Using Diebold and Mariano (1995) test					
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%

	h: the number of periods ahead forecast				
	1	2	3	4	5
Panel B. Using Harvey et al. (1997) test					
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 the –Diebold and Mariano (1995) test. Panel B reports the percentage of ETFs that have significantly lower (higher) MSFE using M2 compared to using M1 indicated by the Harvey et al. (1997) test.
ETF: exchange-traded fund; VAR: vector autoregressive; MAFE: mean absolute forecast error; MSFE: mean squared forecast error.

instance, Phan et al. (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,[8] 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

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

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

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 *MAFE* or the logarithm of the daily *MSFE* (*Ln*(*MSFE*)) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of ETF dollar trading volume; $LogMV_{E,t}$ is the logarithm of ETF market value. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$ and $FixIn_{E,t}$ 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 otherwise. The reference sector in equation (6) is Tax Preferred and the reference style in equation (7) is Small Value.

The regression results of equations (6) and (7) are reported in Table 4, Panels 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*) but negatively correlates with *MAFE*.

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 for mid-cap or small-cap stocks.

Fama and French (1989) and Schwert (2002) find that their models predict that 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 macroeconomic environment. To account for the effect of macroeconomic variables on the predictability of the VAR model in forecasting ETF bid-ask spreads, we regress the following equation

$$
\begin{aligned}
FOR\_ERROR_t = {} & \alpha + \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t \\
& + \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t
\end{aligned} \tag{8}
$$

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 *MAFE* or the logarithm of the daily *MSFE* (*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

Table 4. Effect of ETF characteristics on forecast errors.

	MAFE	*Ln(MSFE)*
Panel A. Effect by ETF sector		
RETVAR	0.029***	34.3***
	(19.44)	(128.7)
LDVOL	−0.122*	0.052***
	(−1.74)	(42.99)
LogMV	−0.842***	−0.21***
	(−6.63)	(−95.01)
Allocation	2.502	0.627***
	(1.55)	(22.18)
Alternative	6.361***	0.699***
	(4.63)	(29.08)
Commodities	12.4***	1.390***
	(6.50)	(41.69)
Convertibles	12.9	1.776***
	(1.57)	(12.36)
Equity	7.236***	1.203***
	(5.57)	(52.93)
FixIn	2.141	0.218***
	(1.60)	(9.32)
Intercept	17.6***	−13.7***
	(10.70)	(−4.76)
N Obs.	806,242	806,242
Adj. R^2	0.0012	0.0742

	MAFE	*Ln(MSFE)*
Panel B. Effect by ETF equity style		
RETVAR	0.063***	71.12***
	(27.69)	(135.97)
LDVOL	0.158**	0.057***
	(2.33)	(36.63)
LogMV	−0.361***	−0.12***
	(−3.00)	(−44.55)
Large_Blend	2.454***	−0.257***
	(2.95)	(−13.44)
Large_Growth	3.314***	−0.048***
	(3.73)	(−2.37)
Large_Value	1.983**	−0.075***
	(2.34)	(−3.84)
Mid_Blend	4.191***	0.358***
	(4.61)	(17.12)
Mid_Growth	3.166***	0.115***
	(3.13)	(4.96)
Mid_Value	2.138**	0.143***
	(2.30)	(6.7)
Small_Blend	2.634**	0.039*
	(2.51)	(1.63)

(Continued)

Table 4. (Continued)

	MAFE	*Ln*(*MSFE*)
Small_Growth	3.542**	−0.015
	(2.57)	(−0.47)
Intercept	9.902***	−13.9***
	(7.88)	(−480)
N Obs.	483,519	483,519
Adj. R^2	0.0018	0.0554

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

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

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 the dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of the market value of ETF. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$ and $FixIn_{E,t}$ 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

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

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 the dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of the 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.
ETF: exchange-traded fund; VAR: vector autoregressive.
***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

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 equation (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 equation (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.

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***	−293.4***	−339.2***
	(2.93)	(3.07)	(2.94)	(−7.45)	(−7.4)	(−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 FEs	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 the 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.
ETF: exchange-traded fund; VAR: vector autoregressive; FEs: fixed effects.
*** and ** represent statistical significance at 1% and 5% respectively.

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 trades compared to other trading schedules. We consider the perspectives of two types of ETF traders including traders who split and do not split their orders.

4.3.1. For ETF traders who split the order. We test whether a trading schedule derived from the model can produce economic benefits for ETF investors wishing to split their orders. Scheduling trades have significant implications for both informed investors (Easley and O'Hara, 1987) and liquidity traders (Admati and Pfleiderer, 1988). Informed investors want to uncover the private information from the order size to maximize gains from trade. Liquidity traders also like to hide their demand for liquidity to avoid front-running and minimize trades' implicit cost (Keim and Madhavan, 1997). Regardless of their reasons to trade, traders frequently 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 90-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, this study first assumes that investors using the VAR model to schedule their trades are traders who split their orders over the trading day. These traders have thirteen 30-minute trading horizons[9] during the trading day, and in each trading horizon, they will trade one-thirteenth of the volume scheduled for the day. The objective is to purchase ETF units at any time during each trading horizon where the bid-ask spread is the lowest. For instance, at 9:30 a.m. on 3 January 2011, an investor wants to trade ETF *i*. The VAR model has five forecasts of bid-ask spread from 9:35 a.m. (1-step ahead forecast) to 9:55 a.m. (5-step ahead forecast). If the current spread at 9:30 a.m. is lower than all *h*-step ahead forecasts, this investor will trade immediately. Otherwise, the investor will choose the time when the bid-ask spread forecast is the lowest to trade. For example, if the 2-step ahead forecast at 9:40 a.m. is the lowest, then the investor will trade at 9:40 a.m. and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 a.m.

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

- 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 et al. (2012), TWAP is one of the main algorithmic trading rules in the stock market.
- *Volume-weighted average price* (VWAP) *trading schedule*: In this trading schedule, an investor is expected to perfectly predict the flows of trading volume during each time interval. At each interval, the investor then allocates the desired trading volume as a fixed proportion of the market volume. As such, this strategy tries to keep steady market participation in each of the intervals.
- *M.A. trading schedule*: In this trading schedule, the trader uses bid-ask spread forecasts from the moving average model to schedule 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 a trader can split an order more frequently than 13 times each trading day. The investor can trade an equal amount of ETF demand for each bid-ask spread quote of the trading day and 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 US 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 four reference trading schedules: *TWAP trading schedule*, *VWAP trading schedule*, *M.A. trading schedule* and *Random trading schedule.* The formula to compute the economic benefit is

Table 6. Economic benefit of the VAR model to trade ETFs.

Time horizon	Average bid-ask spread (in basis points)					Economic benefit			
	AVE_BAS_{VAR}	AVE_BAS_{TWAP}	AVE_BAS_{VWAP}	AVE_BAS_{MA}	AVE_BAS_{Random}	$ECO\_BEN_{VAR,TWAP}$	$ECO\_BEN_{VAR,VWAP}$	$ECO\_BEN_{VAR,MA}$	$ECO\_BEN_{VAR,Random}$
1	38.56	40.27	41.12	40.68	65.52	4.25%	6.23%	5.21%	41.15%
2	32.35	34.19	35.18	36.01	46.71	5.38%	8.04%	10.16%	30.74%
3	31.24	32.79	32.56	34.60	41.92	4.73%	4.05%	9.71%	25.48%
4	30.54	32.02	31.95	33.82	41.08	4.62%	4.41%	9.70%	25.66%
5	30.21	31.46	32.15	33.48	41.03	3.97%	6.03%	9.77%	26.37%
6	30.15	31.44	31.87	33.32	41.74	4.10%	5.40%	9.51%	27.77%
7	29.78	31.05	30.87	33.44	40.18	4.09%	3.53%	10.94%	25.88%
8	30.09	32.29	32.67	33.61	39.72	6.81%	7.90%	10.47%	24.24%
9	29.99	31.19	32.56	33.46	40.24	3.85%	7.89%	10.37%	25.47%
10	29.62	30.90	31.03	33.12	40.65	4.14%	4.54%	10.57%	27.13%
11	29.00	31.29	30.98	35.01	39.99	7.32%	6.39%	17.17%	27.48%
12	132.4	147.4	146.99	88.97	140.1	10.18%	9.93%	-48.81%	5.50%
13	91.69	94.18	94.59	107.82	56.01	2.64%	3.07%	14.96%	-63.70%
Mean	36.16	39.05	39.27	39.43	52.27	7.40%	7.92%	8.29%	30.81%

This table presents the executed bid-ask spread under different trading schedules for an ETF trader who wants to split his order. These trading schedules are as follows:
VAR trading schedule: VAR traders have thirteen 30-minute trading horizons during the trading day, and in each trading horizon, they will trade one-thirteenth of their volume scheduled for the day. The 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 a.m. on 3 January 2011, an investor wants to trade ETF *i*. Based on the VAR model, the investor has five forecasts of bid-ask spread from 9:35 a.m. (1-step ahead forecast) to 9:55 a.m. (5-step ahead forecast). If the current spread around 9:30 a.m. 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 the lowest to trade. For example, if the 2-step ahead forecast at 9:40 a.m. is the lowest, then the investor will trade at 9:40 a.m. and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 a.m.
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 a.m. is the bid-ask spread executed by investors.
VWAP trading schedule: In this trading schedule, trades take place throughout time intervals. Trading volume is allocated according to a fixed proportion of the market volume at each time interval.
M.A. trading schedule: In this trading schedule, traders use bid-ask spread forecasts from the moving average model to schedule their 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 traders can split their orders more frequently than 13 times each trading day. They can trade an equal amount of their order for each bid-ask spread quote of the trading day and 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

$$ECO\_BEN_{VAR,j,t} = \frac{\left(AVE\_BAS_{j,t} - AVE\_BAS_{VAR,t}\right)}{AVE\_BAS_{j,t}} \quad (9)$$

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*.
VAR: vector autoregressive; ETF: exchange-traded fund; TWAP: time-weighted average price; VWAP: volume-weighted average price.

$$ECO\_BEN_{VAR,j,t} = \frac{\left(AVE\_BAS_{j,t} - AVE\_BAS_{VAR,t}\right)}{AVE\_BAS_{j,t}} \tag{9}$$

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.

In the last row in 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% and 7.92%, respectively, compared to using TWAP and VWAP trading schedules 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 traders save their spread costs while allowing them to split their orders over time.

Table 6 also shows the intraday economic benefit patterns using the VAR model's trading schedule compared to other trading schedules. 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 relatively low at the open and lowest at 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.

4.3.2. For ETF traders who do not split the order. 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 et al. (2013) 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 benchmark (e.g. index funds) or because the improved liquidity around this time attracts them. As a result, we expect that scheduling trades at the close would be enticing from the perspective of retail ETF traders who execute only small orders and do 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_{Close}) is only 19.69 basis points, representing a discount of 45% compared to the average bid-ask spread of the VAR trading schedule.[10] When trading at the close, retail ETF traders described above can significantly save up their spread cost compared to splitting trades over the trading day using different trading schedules.

4.4. Spread saving (cost) when prediction interval is correct (wrong)

To give more insights into the economic benefit of the VAR model in predicting ETF bid-ask spread, we provide additional analysis of the spread saving (cost) when the VAR model correctly (incorrectly) predicts the interval associated with the lowest bid-ask spread. At the beginning of

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_{VWAP}	39.27	40.15	41.16
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 rule for all ETFs in the sample. (2) *Cross-sectional average*: First daily executed bid-ask spread is calculated for each ETF as the average of all executed bid-ask spreads during the day (for VAR, TWAP, VWAP and M.A. trading rules). For trading at the close strategy, a daily executed bid-ask spread is the closing bid-ask spread. For a 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 and then the results are averaged cross-sectionally across all ETFs to have the average bid-ask spread for each trading rule. (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.
ETF: exchange-traded fund; VAR: vector autoregressive; TWAP: time-weighted average price; VWAP: volume-weighted average price.

each 30-minute trading horizon, the VAR model produces five bid-ask spread forecasts (corresponding to a 1-step to 5-step forecast ahead at the next 5- to 25-minute intervals). Assuming that the model correctly predicts the 5-minute interval with the lowest actual bid-ask spread, we calculate the spread saving for this trading horizon as follows

$$SPR\_SAVE_{i,t} = \frac{(MIN\_BAS_{i,t} - AVG\_BAS_{i,t})}{AVG\_BAS_{i,t}} \tag{10}$$

where $SPR\_SAVE_{i,t}$ is the spread saving of ETF i at trading horizon t; $MIN\_BAS_{i,t}$ is the actual minimum bid-ask spread during trading horizon t; $AVG\_BAS_{i,t}$ is the average bid-ask spread during trading horizon t excluding the minimum bid-ask spread. Similarly, when the VAR model wrongly forecasts the 5-minute interval with the lowest actual bid-ask spread, the spread loss is computed as follows

$$SPR\_LOSS_{i,t} = \frac{(EXE\_BAS_{i,t} - MIN\_BAS_{i,t})}{MIN\_BAS_{i,t}} \tag{11}$$

where $SPR\_LOSS_{i,t}$ is the spread loss of ETF i at trading horizon t; $MIN\_BAS_{i,t}$ is the actual minimum bid-ask spread during trading horizon t; $EXE\_BAS_{i,t}$ is the bid-ask spread executed at the minimum bid-ask spread interval predicted by the VAR model.

Table 8 reports the average spread saving and spread cost of ETFs in Panels A and B, respectively. As shown in Panel A, the spread saving is highest at the 12th trading horizon (15.51%), followed by the third one (13.24%). Conversely, the spread saving is lowest at the beginning horizon (9.72%) and ending horizon (10.46%). On average, when the VAR model correctly predicts the lowest bid-ask spread interval, investors can save up to 12.51% of their bid-ask spread costs. In Panel B, the figures indicate that investors incur the highest spread loss at the 11th (10.82%) and 12th (12.97%) trading horizons. Similar to Panel A, the lowest spread cost is clustered at the first and last trading horizons with the value of 4.19% and 5.20%, respectively. In summary, wrong

Table 8. Spread saving and spread paid.

Time horizon	MIN_BAS (1)	AVG_BAS (2)	SPR_SAVE (3)
Panel A. Spread saving when the prediction interval is correct			
1	36.12	40.01	9.72%
2	31.28	35.08	10.82%
3	30.15	34.75	13.24%
4	30.12	34.35	12.32%
5	29.95	33.65	10.99%
6	28.91	32.98	12.34%
7	29.54	33.18	10.96%
8	29.75	33.47	11.11%
9	29.06	32.99	11.91%
10	29.04	32.98	11.94%
11	28.53	33.26	14.23%
12	128.32	151.88	15.51%
13	90.31	100.86	10.46%
Average	42.39	48.45	12.51%

Time horizon	EXE_BAS (1)	MIN_BAS (2)	SPR_LOSS (3)
Panel B. Spread cost when the prediction interval is incorrect			
1	37.15	35.66	4.19%
2	32.63	30.85	5.78%
3	32.51	29.75	9.26%
4	32.06	29.73	7.85%
5	31.31	29.57	5.90%
6	30.78	28.52	7.93%
7	30.87	29.17	5.84%
8	31.15	29.36	6.10%
9	30.76	28.71	7.15%
10	30.75	28.68	7.20%
11	31.21	28.16	10.82%
12	143.15	126.72	12.97%
13	93.76	89.12	5.20%
Average	45.24	41.85	8.11%

This table presents the spread saving (cost) when the VAR model accurately (inaccurately) predicts the time interval with the lowest bid-ask spread. If the model correctly predicts the 5-minute interval with the lowest actual bid-ask spread, then the spread saving for this trading horizon is as follows

$$SPR\_SAVE_{i,t} = \frac{(MIN\_BAS_{i,t} - AVG\_BAS_{i,t})}{AVG\_BAS_{i,t}} \tag{10}$$

where $SPR\_SAVE_{i,t}$ is the spread saving of ETF i at trading horizon t; $MIN\_BAS_{i,t}$ is the actual minimum bid-ask spread during trading horizon t; $AVG\_BAS_{i,t}$ is the average bid-ask spread during trading horizon t excluding the minimum bid-ask spread. When the VAR model wrongly forecasts the 5-minute interval with the lowest actual bid-ask spread, the spread loss is computed as follows

$$SPR\_LOSS_{i,t} = \frac{(EXE\_BAS_{i,t} - MIN\_BAS_{i,t})}{MIN\_BAS_{i,t}} \tag{11}$$

(Continued)

Table 8. (Continued)

where $SPR\_LOSS_{i,t}$ is the spread loss of ETF *i* at trading horizon *t*; $MIN\_BAS_{i,t}$ is the actual minimum bid-ask spread during trading horizon *t*; $EXE\_BAS_{i,t}$ is the bid-ask spread executed at the minimum bid-ask spread interval predicted by VAR model.
VAR: vector autoregressive; ETF: exchange-traded fund.

predictions of the lowest bid-ask spread interval from the VAR model would cause ETF investors to pay an average bid-ask spread cost of 8.11% higher than the minimum bid-ask spread. The average spread saving (12.51%) is higher than the spread loss (8.11%), suggesting that the predictions from the VAR model would bring more benefits than costs to ETF investors.

4.5. 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 ETF traders who split their orders. 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 the ETF. In the extreme case that the spread is flat for the whole day, the economic benefit will be zero regardless of the 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 9 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 intraday bid-ask spreads 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 such as Commodities or Equity and lower economic benefit for ETFs such as Tax Preferred or Fixed Income.

To formally test our expectation, we regress the following equation

$$\begin{aligned} ECO\_BEN_{VAR,TWAP,t} = {} & \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} \\ & + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t \\ & + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \end{aligned} \tag{12}$$

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

Table 9. Breakdown of economic benefits.

ETF Spread Volatility Ranking	$ECO\_BEN_{VAR,\ TWAP}$	
	Ranked by RANSPR	Ranked by COVARSPR
Panel A. By spread volatility		
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%

ETF Sector	Number of ETFs	$ECO\_BEN_{VAR,TWAP}$
Panel B. By ETF sector		
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 by 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 by the daily mean bid-ask spread.
ETF: exchange-traded funds; VAR: vector autoregressive; TWAP: time-weighted average price.

difference in the 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 10 reports the regression results of equation (12). 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 smaller size (*LogMV*).

4.6. Predicting ETF liquidity vs predicting stock liquidity

In this subsection, we expand our analysis by applying the VAR model to predict the liquidity of a sample of US stocks. As such, we would be able to contrast the benefits of employing the VAR model in predicting ETF liquidity with those in predicting stock liquidity. To do so, we first divided our sample of ETFs into 150 groups based on their average market capitalization during the sample

Table 10. 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 FEs	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

$$\begin{aligned} ECO\_BEN_{VAR,TWAP,t} = {} & \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} \\ & + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t \\ & + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \end{aligned} \tag{12}$$

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 the 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.
VAR: vector autoregressive; TWAP: time-weighted average price; ETF: exchange-traded fund.
***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

Table 11. Results of predicting stock liquidity.

	h: the number of periods ahead forecast				
	1	2	3	4	5
Panel A. Stocks with better h-step forecast using the VAR model					
Number of stocks have lower MAFE using M2 than M1	123	115	101	95	77
Percentage of stocks have lower MAFE using M2 than M1	82%	76.67%	67.33%	63.33%	51.33%
Number of stocks have lower MSFE using M2 than M1	110	99	92	81	63
Percentage of stocks have lower MSFE using M2 than M1	73.33%	66%	61.33%	54%	42%
Total number of stocks	150	150	150	150	150

	h: the number of periods ahead forecast				
	1	2	3	4	5
Panel B. Results of Diebold and Mariano's (1995) test					
Proportion of stocks have significantly *lower* MAFE using M2 than M1	73.33%	70.67%	60.67%	52.67%	42.67%
Proportion of stocks have significantly *higher* MAFE using M2 than M1	2.00%	4.00%	6.67%	13.33%	22.67%
Proportion of stocks have significantly *lower* MSFE using M2 than M1	63.33%	58.00%	52.00%	43.33%	30.00%
Proportion of stocks have significantly *higher* MSFE using M2 than M1	2.67%	5.33%	8.00%	15.33%	27.33%

Time interval	Average bid-ask spread (in basis points)					Economic benefit			
	AVE_ BAS_{VAR}	AVE_ BAS_{TWAP}	AVE_ BAS_{VWAP}	AVE_ BAS_{MA}	AVE_ BAS_{Random}	ECO_ $BEN_{VAR,TWAP}$	ECO_ $BEN_{VAR,VWAP}$	ECO_ $BEN_{VAR,MA}$	ECO_ $BEN_{VAR,Random}$
Panel C. Economic benefit									
Mean	48.23	55.24	54.42	57.58	61.12	12.69%	11.37%	16.24%	21.09%

This table presents the performance of the VAR model in predicting stock bid-ask spread. Panel A shows the number and the percentage of stocks having lower MAFE or MSFE using M2 compared to M1. Panel B reports the percentage of stocks which have significantly lower (higher) MAFE or MSFE using M2 compared to using M1 indicated by the Diebold and Mariano (1995) test. Panel C presents the executed bid-ask spread under different trading schedules for stock traders who want to split their order. The explanation of items in Panel C is the same as in Table 6.
VAR: vector autoregressive; TWAP: time-weighted average price; MAFE: mean absolute forecast error; MSFE: mean squared forecast error.

period between 2011 and 2017. For each ETF group, we select a US stock whose average market capitalization closely matches the group's average market capitalization. The procedure results in a sample of 150 US stocks. The intraday trading data of these stocks are then collected using the Thomson Reuters Tick History database.

We re-apply the VAR model as specified in equation (1) to predict stock liquidity. The results are summarized in Table 11. In Panel A, we find that the VAR model (i.e. M2) is substantially more efficient than the MA model (i.e. M1) in predicting stock liquidity. The percentage of stocks having lower MAFE and MSFE using M2 than M1 is over 50% for all forecast horizons, except for using MSFE at a 5-step forecast. In Panel B, the results of Diebold and Mariano's (1995) test further confirm the superiority of the VAR model over the MA model. Compared to the results for ETFs in Tables 2 and 3, the statistical outperformance of the VAR model in forecasting stock liquidity is more robust and observable for the most number of periods ahead of forecast. In Panel C, we reveal that investors employing the VAR model to schedule stock trading can save up to 12.69% and 11.37%, respectively, compared to the TWAP and VWAP trading schedules. These numbers are significantly higher than the spread savings for ETFs, suggesting that the VAR model might bring more economic benefit to stock investors than ETF traders. The inferior economic benefit of the VAR model for ETF traders might be explained by the fact that the model does not capture the impact of creation/redemption activities, which are considered important drivers of ETF bid-ask spread.

Besides, we also investigate the determinants of forecast errors of the VAR model in predicting stock liquidity. For the sake of brevity, the details of the regression models and their results are reported in Appendix 4. Except for the impact of the short rate, we find that the effects of other macroeconomic variables and stock characteristics on forecast errors of stocks are mostly consistent with those of ETFs.

5. Conclusion

Despite the growing importance of trading ETFs, there is little evidence of the predictability of ETF bid-ask spread. Our article 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 1350 US 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 the traders' type. For ETF traders who split orders to hide their trading motives, the VAR trading schedule is superior to other trading schedules. For ETF traders who do not possess private information and trade 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. In a further cost–benefit analysis, we show that the spread savings of the VAR model from accurately predicting the time intervals with the lowest bid-ask spread are considerably higher than the spread costs incurred when the model incorrectly calls these intervals.

Furthermore, 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 ETFs and stocks could be the spread volatility. When security exhibits more bid-ask spread volatility, it would 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. Finally, employing a sample of US stocks, we find evidence that the VAR model works better in predicting stock liquidity than ETF liquidity. More uncertainty in predicting ETF liquidity could be explained by the effects of creation/redemption in shaping ETF bid-ask spreads, which are not captured in the VAR model.

Finally, there are several interesting future research one might take when examining the predictability of ETF liquidity. First, in this study, we assume the ETF bid-ask spread is a function of mid-quote volatility, trading volume, number of trades and lagged bid-ask spreads. However, this list of the explanatory variables of the ETF bid-ask spread is not exhaustive. Depending on the availability of intraday data, the inclusion of other explanatory variables such as ETF pricing errors and intensity of creation/redemption activities could improve the VAR model's predictability.

Second, as the forecast errors from the VAR model are relatively high, future studies may apply Ridge, LASSO, or Elastic Net penalized regressions to the prediction models. It would be interesting to assess whether these models could achieve better prediction results.

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Notes

1. https://www.nyse.com/data-insights/etfs-rising-in-the-turbulence
2. 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).
4. https://www.etftrends.com/esg-channel/how-investors-turned-to-etfs-for-liquidity-and-market-access-in-2020/
5. Taylor (2002) finds that using predictions of bid-ask spreads from a vector autoregressive (VAR) model can save up 34% of spread costs for London Stock Exchange (LSE) stocks. Groß-KlußMann and Hautsch (2013) use a long-memory autoregressive conditional Poison model to predict the bid-ask spreads of four US mid-cap stocks and find that the predictions from their model can help traders save 8.4% to 10.9% of spread costs.
6. Breen et al. (2002) define Net turnover as buyer-initiated volume less seller-initiated volume as a fraction of shares outstanding.
7. For instance, the first $\sigma_{i,t}$ of each day is calculated as the standard deviation of midpoint quotes between 9:30 a.m. and 9:35 a.m.
8. See Agrrawal and Clark (2009), Rompotis (2010) and Calamia et al. (2013).
9. These 13 trade horizons are equivalent to thirteen 30-minute time intervals during the trading day.
10. Our regression of the intraday pattern of exchange-traded fund (ETF) liquidity in Appendix 2 shows that the time-weighted bid-ask spread tends to be low during the last 15-minute interval.

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Appendix 1

Time-weighted bid-ask spread and dollar volume-weighted effective spread.

Year	Number of ETFs	BAS (in bps)	*ESpread* (in bps)
Panel A. By year			
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	1245	37.48	20.26

ETF sector	Number of ETFs	BAS (in bps)	*ESpread* (in bps)
Panel B. By ETF sector			
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 the 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 calculations. 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.
ETF: exchange-traded funds.

Appendix 2

Intraday patterns of ETF liquidity.

Independent variables	BAS	*ESpread*
	(1)	(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

$$S_{i,j,d} = \alpha + \sum_{j=1}^{4} \beta_j D_j + \sum_{j=25}^{26} \beta_j D_j + Exch\_Dummy_i + \varepsilon_{i,i,d} \tag{13}$$

where $S_{i,j,d}$ is the spread of ETF *i* during interval *j* of day *d* with spread being 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 *j*th interval, and 0 otherwise. Each trading day is divided into twenty-six 15-minute time intervals. $Exch\_Dummy_i$ has a value of 1 if ETF *i* is listed on NASDAQ and 0 if listed on NYSE.
ETF: exchange-traded funds; BAS: bid-ask spread.
*** represent statistical significance at 1%.

Appendix 3

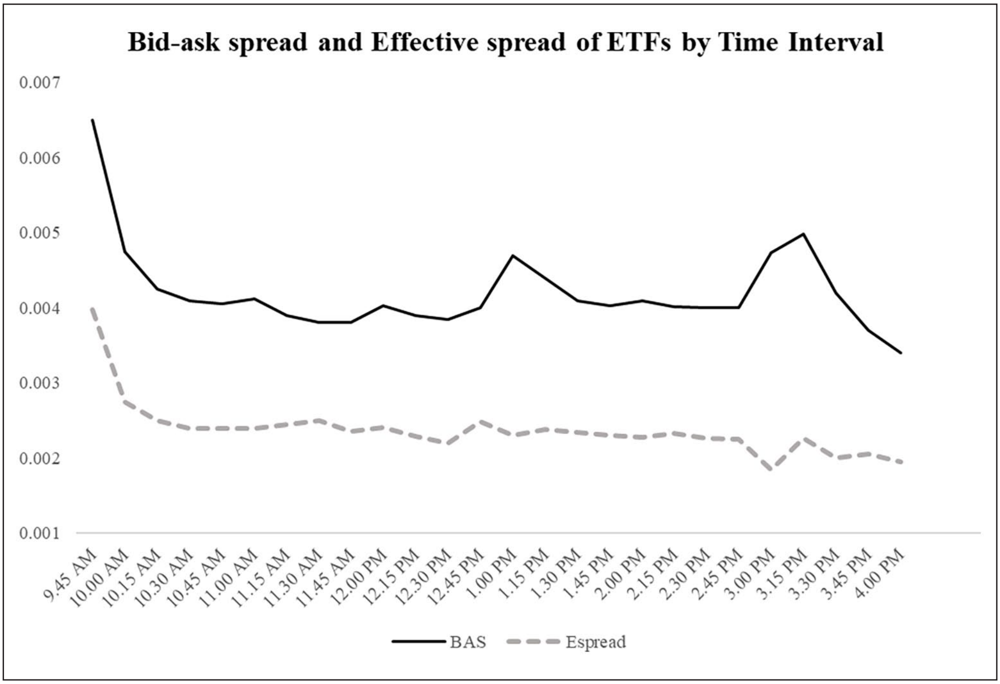

Figure of intraday pattern of ETF liquidity.
This figure shows the intraday pattern of time-weighted bid-ask spread (BAS: the blue line) and dollar volume-weighted effective spread (ESpread: the red line) of 1350 ETFs over the period between 2011 and 2017. The trading time starts from 9:30 a.m. to 4:00 p.m. and is divided into twenty-six 15-minute time intervals.

Appendix 4

Determinants of forecast errors: stock sample.

Independent variables	Using *MAFE*			Using *Ln*(*MSFE*)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Effects of stock characteristics						
RETVAR	0.049***	0.051***	0.044***	50.12***	52.12***	49.11***
	(8.41)	(8.65)	(7.92)	(18.22)	(19.32)	(17.18)
LDVOL	0.082	0.106	0.042	0.031***	0.037***	0.032***
	(1.03)	(1.58)	(0.35)	(31.23)	(32.14)	(31.56)
LogMV	−0.324***	−0.335***	−0.311***	−0.121***	−0.133***	−0.126***
	(−4.52)	(−4.89)	(−4.01)	(−10.53)	(−11.35)	(−10.98)
Stock FE	No	Yes	No	No	Yes	No
Year FE	No	No	Yes	No	No	Yes
N Obs.	180,350	180,350	180,350	180,350	180,350	180,350
Adj. R^2	0.0031	0.0036	0.0030	0.0893	0.0932	0.0912

Independent variables	Using *MAFE*			Using *Ln*(*MSFE*)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. Effect of macro-economic conditions						
WRET	−0.312	−0.302	−0.314	−4.329***	−4.451***	−4.317***
	(−1.52)	(−1.49)	(−1.54)	(−7.23)	(−7.35)	(−7.19)
WARET	3.523***	3.215***	3.612***	99.14***	95.31***	98.12***
	(3.15)	(3.04)	(3.41)	(34.11)	(30.12)	(33.93)
WVARRET	0.812***	0.834***	0.815***	−239.1***	−182.3***	−238.5***
	(3.95)	(4.15)	(4.01)	(−6.54)	(−5.14)	(−6.32)
ShortRate	−0.031	−0.032	−0.031	−0.124	−0.083	−0.121
	(−0.12)	(−0.13)	(−0.12)	(−1.53)	(−0.98)	(−1.49)
TermSpread	−0.001	−0.001	−0.001	0.094	0.063	0.091
	(−0.03)	(−0.04)	(−0.03)	(0.45)	(0.31)	(0.42)
DefaultSpread	0.149***	0.153***	0.150***	0.231***	0.421***	0.398***
	(2.90)	(2.99)	(2.96)	(12.41)	(17.42)	(16.11)
Stock FE	No	Yes	No	No	Yes	No
Year FE	No	No	Yes	No	No	Yes
N Obs.	180,145	180,145	180,145	180,145	180,145	180,145
Adj. R^2	0.0052	0.0061	0.0051	0.0141	0.0232	0.0142

Panels A and B of Appendix 4 present the regression results of the following model

$$FOR\_ERROR_{S,t} = \alpha + \beta_1 RETVAR_{S,t} + \beta_2 LDVOL_{S,t} + \beta_3 LogMV_{S,t} + \epsilon_t \tag{14}$$

$$\begin{aligned} FOR\_ERROR_{S,t} = \alpha &+ \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t \\ &+ \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t \end{aligned} \tag{15}$$

where $FOR\_ERROR_{S,t}$ is the 1-step ahead forecast error of the VAR model to predict stock 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. $RETVAR_{S,t}$ is the 5-day return variance of ETF; $LDVOL_{S,t}$ is the logarithm of the dollar trading volume 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 the 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.
FE: fixed effects.
*** represent statistical significance at 1%.