Research

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Active Trading in ETFs: The Role of High-Frequency Algorithmic Trading

Archana Jain, Chinmay Jain, and Christine X. Jiang

Archana Jain is an associate professor of finance at Saunders College of Business, Rochester Institute of Technology, Rochester, New York. Chinmay Jain is an assistant professor of finance at the State University of New York at Geneseo School of Business, Geneseo, New York. Christine X. Jiang is a professor of finance at Fudan University, Shanghai.

In the study reported here, we explored high-frequency algorithmic trading and its effect on exchange-traded funds (ETFs). Using the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size as proxies for algorithmic trading, we found that more algorithmic trading in ETFs results in smaller and less persistent deviations of fund prices from their net asset values (NAVs). Arbitrage strategies adopted by algorithmic traders directly help reduce the magnitude and persistence of ETF price deviations from NAVs. Also, algorithmic trading improves ETF liquidity by lowering spreads and facilitates arbitrage.

Both high-frequency algorithmic trading[1] and the assets of exchange-traded funds (ETFs) have grown exponentially in size and trading volume over the last decade. According to several reports (e.g., Breckenfelder 2019, Vlastelica 2017), high-frequency algorithmic trading accounts for 50% of trading volume in the US stock market. Worldwide ETF assets grew from approximately $1 trillion in 2009 to more than $6 trillion in 2020.

The liquidity of ETFs has made them attractive for trading by high-frequency algorithmic traders. Given the often controversial role of high-frequency trading in equity markets, a concern that high-frequency algorithmic trading may exacerbate ETF volatility and mispricing has been raised. We studied the interaction of high-frequency algorithmic trading and ETFs and show that high-frequency algorithmic trading improves ETF price efficiency through arbitrage strategies that keep ETF prices aligned with the values of their underlying assets, or net asset value (NAV).

Typically, ETFs trade at prices close to their NAVs. Price deviations from NAV, however, can be large for some categories of ETFs, such as ETFs holding non-US or illiquid assets, and can be large during times of market stress (Petajisto 2017). As a result, an investor may pay a premium for buying an ETF or may have to sell the ETF at a discount. For example, ETF prices deviated significantly from their underlying NAVs during the flash crash in May 2010. During the 2020 COVID-19 pandemic, prices of some bond ETFs differed substantially from their NAVs, necessitating the US Federal Reserve to step in and buy $8.7 billion worth of bond ETFs to support the prices of the underlying securities. Trading prices of ETFs have become a growing topic of discussion, as evidenced by the 2020 recommendation of

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the SEC Asset Management Advisory Committee to investigate divergence in ETFs' prices from their NAVs (see SEC 2020).

Why is it important that ETF prices remain aligned with their NAVs? At the market level, ETF price inefficiency can propagate risk into underlying assets, which leads to market instability and distorts individual assets' prices. At the investor level, price inefficiency means that an investor might trade at unfavorable prices, thus taking on added risk when buying or selling an ETF. Between 2004 and 2015, about 38% of actively managed mutual funds also held ETFs in their portfolios (Sherrill, Shirley, and Stark 2017), making ETF price efficiency a significant concern not only for retail investors but also for fund managers.

What mechanisms work to reduce deviations of ETF prices from NAVs? Divergences between ETF prices and NAVs present arbitrage opportunities. For example, in the case of an ETF price premium (discount), arbitrageurs can simultaneously sell (buy) the ETF and buy (sell) the underlying assets. Bhattacharya and O'Hara (2018) showed that the limitation of the ETFs' arbitrage mechanism can lead to market instability. Many analysts believe authorized participants (APs)[2] and their primary market transactions (redemptions and creations) are the essential market force to keep ETF prices aligned with NAVs. Pan and Zeng (2020) posited, however, that intraday arbitrage occurs even before APs have a chance to profit from the creation/redemption of new units at the end of the day.

We show that high-frequency algorithmic trading on small deviations in ETF prices through intraday arbitrage can prevent the NAV deviation from increasing, thereby improving price efficiency. We shed light on the following questions: How pervasive is high-frequency algorithmic trading in ETFs? Does high-frequency algorithmic trading affect the efficiency of ETF prices? What are the channels for high-frequency algorithmic traders to influence the efficiency of ETFs?

We first identified the prevalence of high-frequency algorithmic trading in ETFs. Because these data do not readily exist, our empirical strategy was to begin with the SEC Market Information Data Analytics System (MIDAS) by using widely accepted proxies for algorithmic trading (Hendershott, Jones, and Menkveld 2011; Weller 2018). In addition, we used various cutoffs to detect the faster trades, those that are probably high-frequency trades.[3] For the remainder of this article, we use the term "algorithmic trading" (AT) broadly to signify high-frequency algorithmic trading.

In a data sample from 2012 to 2018, we found a large amount of algorithmic trading in ETFs. The average cancel rate (the rate at which orders are canceled) was 464, significantly higher than the 25 for stocks reported in Jain, Jain, and Jiang (2017). Our sample reflected a relatively small value-weighted ETF discount and premium, averaging about 2.2 basis points (bps), and the standard deviation was 3.44 bps. The equal-weighted deviation was higher, at 3.66 bps, suggesting that small funds tend to have larger deviations from NAV than large funds. The average persistence of deviation in our sample was about 5.8 days. An asymmetrical pattern, however, characterized the persistence of discounts versus the persistence of premiums.

In this article, we show that increased algorithmic trading lowers the magnitude and persistence of price deviations for ETFs, which is consistent with empirical evidence on the positive impact of AT on market quality measures, such as short-term volatility, spreads, and displayed depth (Hendershott et al. 2011).

We also performed additional analyses to better understand the channels through which algorithmic trading could affect ETF price efficiency. We conjectured that AT influences ETF prices through two main mechanisms: (1) intraday arbitrage that keeps ETF prices aligned with NAVs and (2) reduced spread that further facilitates arbitrage activity. Our results clearly show the importance of intraday arbitrage by AT. We also found that AT indeed reduces spreads, which supports the notion that AT plays the role of market maker. This function of AT eases the limits to arbitrage resulting from transaction costs, thus further reducing deviations.

Our findings provide new insights into the impact of algorithmic trading on ETF price efficiency. We are the first to show that AT is highly prevalent in ETFs. Furthermore, we found that ETF prices are generally efficient and that AT plays a critical role in improving ETF price efficiency through intraday arbitrage, a role traditionally attributed to APs. Finally, we found that AT improves ETF market liquidity, narrowing spreads and providing investors with additional benefits in trading ETFs.

As the popularity of ETFs among investors has grown, investor understanding of the price efficiency of ETFs and the mitigation of costs from ETF mispricing has become increasingly important. Our results show that in the presence of algorithmic trading, investors can be confident that the prices they transact at are close to NAVs and arbitragers can trade freely because of lower transaction costs. For institutional investors that trade heavily in ETFs, examining the prevalence of AT can help them understand ETF pricing and detect mispricing. Although many analysts believe that AT can harm investors by distorting prices and increasing volatility, we are able to inform regulators and the broader investment management community that AT plays a productive and essential role in improving ETF price efficiency. In fact, restrictions on AT in capital markets may actually increase market instability by preventing key arbitrage mechanisms from functioning.

Data and Descriptive Statistics

Our initial sample comprised US equity ETFs downloaded from ETFdb.com. Our sample period is January 2012 through June 2018. We dropped leveraged and inverse ETFs. We also dropped days with only a single trade or no trade from nonhidden orders. We downloaded the NAV data from Bloomberg. Following Petajisto (2017), we dropped ETF-days with ETF premiums/discounts above 20%. Our sample after these changes comprised 623 equity ETFs.

We downloaded the data from MIDAS, which collects and processes data from the consolidated tapes and from the separate proprietary feeds made available by each equity exchange. Specifically, MIDAS collects posted orders and quotes on national exchanges, modifications/cancellations of those orders, trade executions against those orders, and off-exchange trade executions. We retrieved cancellations, trades, trade volume, order volume, odd-lot volume, and trade size for 13 US exchanges from MIDAS.

We downloaded closing prices, high prices, low prices, closing ask prices, closing bid prices, and shares outstanding from CRSP.

We trimmed all the variables at the 1st and 99th percentiles, which eliminated a few ETFs with only outlier values, resulting in a final sample of 578 ETFs. Appendix A provides details of our sample selection. The size of our equity ETF sample is similar to the sample in Huang, O'Hara, and Zhong (forthcoming), who covered 508 equity funds, and Da and Shive (2018), who covered 549 ETFs.

In **Table 1**, we provide means, medians, and standard deviations of ETF fund characteristics in Panel A and of algorithmic trading in ETFs in Panel B. The variables are defined in Appendix A. For each day, we took value-weighted or equal-weighted means or medians across ETFs to calculate daily values. In Table 1, we report the time-series averages of these daily means and medians for our sample. For each day, we also took the standard deviation across ETFs to calculate daily values and report the time-series averages of these daily standard deviations for our sample. The value-weighted (equal-weighted) average of assets under management (AUM) for our sample, calculated as price times shares outstanding, is approximately $9.5 billion ($1.7 billion), with a median of about $7.4 billion ($0.4 billion). The value-weighted (equal-weighted) mean value of turnover, calculated as trade volume divided by shares outstanding, is 0.60% (0.49%). The value-weighted (equal-weighted) mean value of volatility, calculated as the difference between the high price and low price divided by the high price, is 0.99% (1.02%). The absolute deviation from NAV was calculated as the absolute difference between the quote midpoint and the NAV of the ETF divided by the quote midpoint, multiplied by 100.[4] For our sample, the value-weighted (equal-weighted) mean value of the absolute deviation is 2.20 bps (3.66 bps), with a median of 1.75 bps (2.62 bps). The value-weighted (equal-weighted) mean of raw deviations is 0.41 bp (0.60 bp), with a median of 0.35 bp (0.48 bp). On average, a run of particular deviation persisted for 5.8 days on a value-weighted basis and 10.2 days on an equal-weighted basis.[5] We also report the deviation separately for ETFs traded at a discount and ETFs traded at a premium. The value-weighted (equal-weighted) mean discount is 1.95 bps (3.33 bps), and it lasted for about 5 days (9 days), on average; the mean premium is 2.20 bps (3.75 bps), which lasted for about 7 days (11 days), on average.

Deviations are small in magnitude but higher than zero for diversified equity ETFs and similar to the deviations for sector ETFs of 2 bps reported in Petajisto (2017) for a sample period of 2007–2014. Thus, the deviations in Table 1 do not show a decline over time. Interestingly, standard deviations of the discount/premium are much smaller in our sample—1.96 bps on a value-weighted basis and 3.44 bps on an equal-weighted basis—than the range between 9 bps and 42 bps in Petajisto (2017).

We also examined in detail the persistence of premiums and discounts to NAV. We counted the number

Table 1. Descriptive Statistics, 2012–2018

	Value Weighted			Equal Weighted		
Variable	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
A. ETF fund characteristics						
AUM ($ thousands)	9,511,054	7,441,882	7,920,077	1,670,429	386,202	3,619,338
Turnover (%)	0.60	0.23	1.12	0.49	0.15	1.20
Volatility (%)	0.99	0.92	0.33	1.02	0.94	0.47
Abs. deviation from NAV (%)	0.0220	0.0175	0.0196	0.0366	0.0262	0.0344
Raw deviation from NAV (%)	0.0041	0.0035	0.0262	0.0060	0.0048	0.0477
Persistence of deviation (days)	5.8	3.6	7.4	10.2	5.1	13.5
Discount to NAV (%)	−0.0195	−0.0145	0.0186	−0.0333	−0.0235	0.0316
Persistence of discount (days)	4.8	3.2	5.9	9.2	4.6	12.2
Premium to NAV (%)	0.0220	0.0169	0.0204	0.0375	0.0269	0.0356
Persistence of premium (days)	7.2	4.6	8.4	11.2	6.2	13.8
B. Algorithmic trading						
Cancels	388,880	314,694	303,898	126,946	51,796	195,334
Lit trades	3,158	1,471	4,692	773	53	2,647
Cancel rate	464	220	962	1,748	777	2,563
Trade volume (thousands)	650	247	1,157	162	10	625
Order volume (thousands)	252,864	214,990	189,579	104,700	52,103	136,062
Trade-to-order ratio (%)	0.23	0.13	0.27	0.09	0.03	0.19
% odd-lot volume	6.40	4.91	5.55	8.38	5.28	9.98
Trade size	180	159	87	192	154	130
Order fragmentation	0.7739	0.7934	0.0815	0.7287	0.7594	0.1208

AUM = assets under management.

Notes: We calculated cross-sectional value-weighted and equal-weighted means, medians, and standard deviations for all variables for each day. We report here the time-series means of those daily values. Appendix A contains variable definitions and sample details. The row “Cancels” is the number of orders that were canceled before execution. The row “Lit trades” is a count of all trade messages for trades that were not against hidden orders.

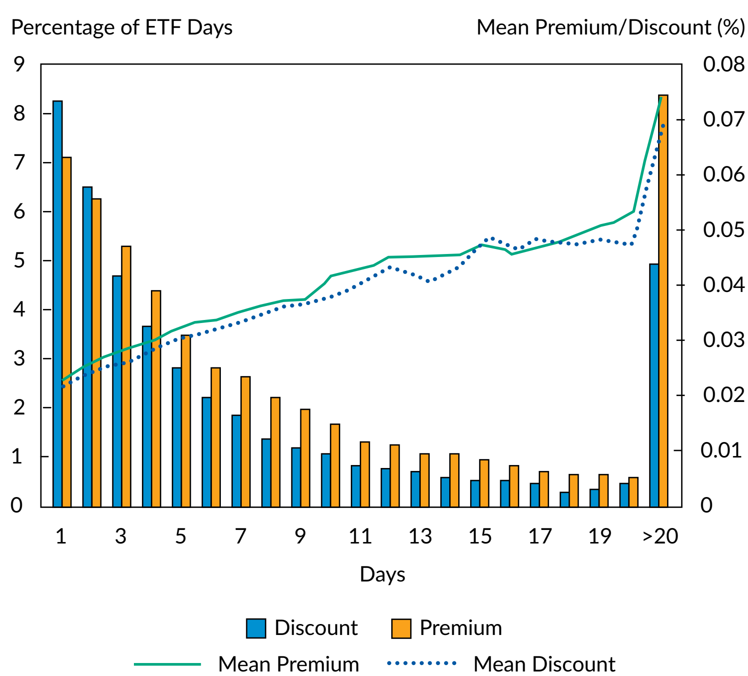
of days in each run of deviation between the ETF's NAV and price. In **Figure 1**, we report the percentage of ETF-days of various lengths for which the deviation from NAV lasted in one run. For example, 7.18% of the observations had a premium (and 8.32% had a discount) for only one day, as represented in the first bars in Figure 1. Most of the deviations lasted for fewer than 10 days. Only 17.58% of our sample observations had a premium or discount that lasted more than 10 days in one run. Some 37.34% of the observations had deviations that lasted 2–5 days in one run, and 19.13% of observations had deviations that lasted 6–10 days in one run.

Figure 1 also shows a plot of the mean values of the premiums or discounts. We found the average daily deviation to be higher the longer it lasted. The mean discount is reported as 2.23 bps when it lasted for one day, but it is 6.96 bps when it lasted for more than 20 days. Similarly, the mean premium is shown as 2.37 bps when it lasted for one day, but it is 7.60 bps when it lasted for more than 20 days.

Panel B of Table 1 provides data on algorithmic trading in ETFs. Following Jain et al. (2017) and Weller (2018), we used the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size as proxies for AT. We calculated the cancel rate as cancels (the number of orders canceled before execution) divided by lit trades (trade messages for trades that were not against hidden orders). A higher cancel rate indicates higher AT. Trade volume is the number of shares traded. Order volume is the volume of total orders placed. The trade-to-order ratio was calculated as trade volume divided by order volume times 100. A lower trade-to-order ratio indicates higher AT. Odd-lot trades are defined as trades of less than 100 shares. Percentage odd-lot volume was calculated as the volume of odd-lot trades divided by total trading volume times 100. A higher percentage odd-lot volume indicates higher AT. Trade size was calculated as lit trade volume divided by lit trades. A lower trade size indicates higher AT.

Following Madhavan (2012), we included order fragmentation as another proxy for AT.[6] Order fragmentation captures the competition among traders for order flow and aggressive quote behavior. Higher order fragmentation indicates more algorithmic trading. Thus, it is a better proxy for the dynamics of AT than is trade volume fragmentation (Madhavan). The Herfindahl–Hirschman Index (HHI), a measure of concentration, ranges from 0 to 1. The higher figures indicate less fragmentation in a particular ETF. Order fragmentation was measured as 1 minus the HHI for order volume across all the exchanges. The order fragmentation data we found (0.77 for the value-weighted mean and 0.73 for the equal-weighted mean) are higher than the quote fragmentation of 0.65 reported in Madhavan for the period of 20 trading days (7 April 2010–5 May 2010). This finding suggests that markets are becoming increasingly fragmented over time. Note that we used

Figure 1. Persistence of Premiums and Discounts to NAV, 2012–2018



SEC MIDAS data, which is a daily level, whereas Madhavan used NYSE T&Q (Trade and Quote) data.

Results

We report our findings related to algorithmic trading activity in ETFs by exchange, ETF deviations and persistence by market and ETF characteristics, the effect of AT on deviations from NAV and on persistence of deviations, and the results of a series of tests—a double-sort analysis based on AT and spread, a mediation analysis to test the arbitrage and market-making effects of algorithmic trading on deviations from NAV and its persistence, and several robustness tests.

AT Activity in ETFs by Exchange. In **Table 2**, we present descriptive statistics for the algorithmic trading variables by exchange. For each day, we took the value-weighted mean for each exchange to calculate daily values. We report time-series averages of these daily mean values for our sample. We also calculated the venue shares of the US equity market based on reported trade volume and order volume. Market share by exchange for trades is defined as trade volume for the exchange divided by the total trade volume. Market share by exchange for orders is defined as order volume for the exchange divided by the total order volume. We found that, on average, NYSE Arca, with 31.53% market share for trade volume and 26.92% market share for order volume, is the leading exchange for both trading and order placement for ETFs. Nasdaq is the next leading exchange. In contrast, when it comes to stocks, the NYSE leads for trade volume and Nasdaq leads for order volume (Jain et al. 2017).

We also examined the total number of times each exchange dominated for a given ETF (the exchange that had the highest trade volume), and the results are plotted in **Figure 2**. As shown, for all the

Table 2. Descriptive Statistics of Algorithmic Trading in ETF by Exchange, 2012–2018

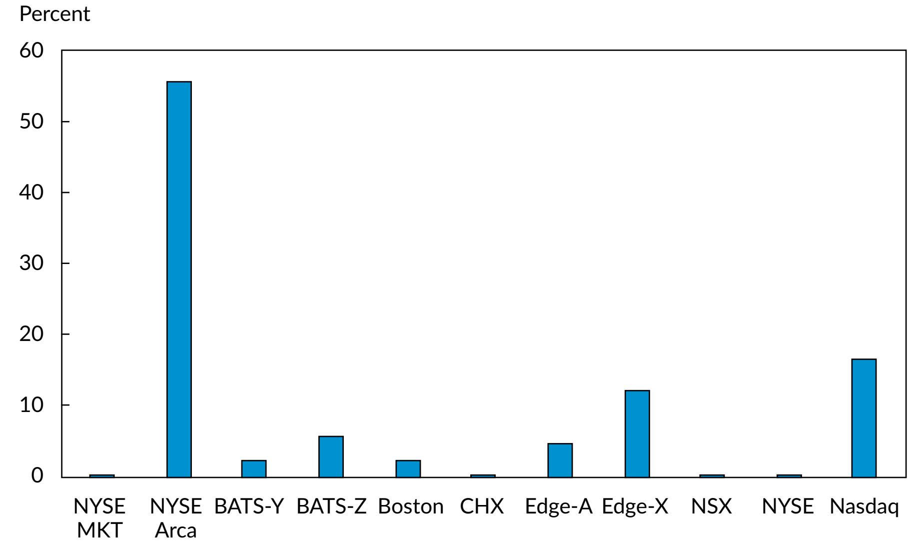
	Cancel Rate	Trade-to-Order Ratio	% Odd-Lot Volume	Trade Size	Market Share by Exchange for Trades	Market Share by Exchange for Orders
NYSE MKT[a]	200	7.41%	14.1%	110	0.29%	0.27%
NYSE Arca	360	0.42	5.8	228	31.53	26.92
BATS-Y[b]	489	0.54	8.6	160	5.41	5.97
BATS-Z	520	0.41	5.8	217	16.21	16.87
Boston	464	0.47	8.9	170	4.12	5.29
Chicago Stock Exchange (CHX)	830	8.93	1.8	809	1.33	7.33
Edge-A[b]	552	0.47	6.1	196	5.68	6.31
Edge-X	293	0.63	5.4	223	13.98	10.10
National Stock Exchange (NSX)	675	1.70	3.6	356	0.85	1.83
NYSE[a]	147	4.87	15.9	102	0.74	0.57
Nasdaq	426	0.44	6.3	215	20.28	18.93
Philadelphia Stock Exchange (Phlx)	836	0.52	7.1	261	2.15	5.27

Note: Appendix A contains variable definitions and sample details.

[a]NYSE and NYSE MKT use the level-book method, in which a message is printed for every event that affects the order book at a given price point for each stock, but this method does not print distinct order messages with their own order IDs; other exchanges use the more granular order-based method. This approach prints a message for every displayed quote or order (i.e., orders that are not immediately executable and not denoted as hidden).

[b]BATS-Y (BATS stands for Better Alternative Trading System) and Edge-A are taker–maker fee venues. Taker–maker is also known as "payment for order flow." *Makers* provide two-sided markets, thus delivering liquidity. *Takers* are those trading the prices set by market makers.

Figure 2. Frequency Distribution of Dominating Exchanges, 2012–2018



Note: Number of days for which each of 11 exchanges was the dominating exchange for our sample.

ETF-days in our sample, NYSE Arca dominated, followed by Nasdaq. The next two most dominant exchanges are Edge-X and BATS-Z.[7]

AT in ETFs, ETF Deviations, and Persistence.

In **Table 3**, we present data on how algorithmic trading and ETF characteristics varied over time and across days in our sample for various return and volatility distributions. We report the value-weighted means of the cancel rate, the trade-to-order ratio, and so forth, by year and by market characteristic. Panel A contains the data by year. We expected AT to increase over time as computer algorithms started replacing human traders. We expected deviations from NAV and the persistence of those deviations to lessen over time because of increased AT. We found that cancel rates have generally increased since 2013, indicating higher AT over the years. The trade-to-order ratio in Table 3 varies from 0.17% to 0.28% over these years, and it has been decreasing since 2015, indicating increased AT since then. Percentage odd-lot volume has generally increased over the years, whereas trade size has generally decreased, indicating increased AT. Markets have become more and more fragmented over the years. The absolute deviation from NAV declined from 2.74 bps in 2012 to 1.88 bps in 2017, and it was slightly higher in 2018 than in 2017. No clear pattern in persistence of those deviations is shown.

In Panel B of Table 3, we present these variables for various market return percentiles. The data for the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size on extreme return days point to increased algorithmic trading on those days. We found the markets to be more fragmented during both extreme positive-return and extreme negative-return days. Absolute deviation from NAV is shown to have been higher on days of extreme returns, but the persistence of those deviations is somewhat lower.

In Panel C of Table 3, we present the numbers by market volatility, proxied by the VIX (the Cboe Volatility Index). Cancel rates were generally higher for higher market volatility, indicating more algorithmic trading on those days. The trade-to-order ratio generally decreased with higher market volatility, again indicating higher AT on those days. Data for percentage odd-lot volume and trade size reflect no clear pattern. Order fragmentation generally increased with increases in market volatility, which indicates that markets were more fragmented on days of higher volatility. Absolute deviation from NAV was higher for days with higher market volatility. No clear pattern is shown for the persistence of those deviations.

Table 4 contains the sample data organized by ETF characteristics, such as AUM, volatility, turnover, and age, to see how algorithmic trading varies with these variables. For Panels A–C, we divided the sample into quartiles to create ranks based on AUM, volatility, and turnover, and in Panel A, we present the variables by AUM ranks of ETFs. The cancel rate was lower, the trade-to-order ratio was higher, and

Table 3. Algorithmic Trading, ETF Deviation, and Persistence of Deviation over Time and by Market Characteristic, 2012–2018

	Cancel Rate	Trade-to-Order Ratio	% Odd-Lot Volume	Trade Size	Order Fragmentation	Absolute Deviation from NAV	Persistence of Deviation
A. By year							
2012	475	0.17%	4.0%	216	0.7277	0.0274%	5.0
2013	324	0.27	5.0	201	0.7246	0.0244	6.6
2014	369	0.28	6.0	189	0.7496	0.0218	6.3
2015	481	0.25	7.7	163	0.8215	0.0209	5.6
2016	541	0.24	5.9	170	0.8078	0.0191	5.4
2017	500	0.22	7.9	159	0.7947	0.0188	5.6
2018	652	0.19	10.0	141	0.8082	0.0210	6.3
B. By market (i.e., S&P 500 Index) return category							
Bottom 1 percentile	655	0.16%	7.5%	169	0.7861	0.0319%	5.5
Bottom 5 percentile	571	0.18	7.1	172	0.7900	0.0267	5.5
Bottom 10 percentile	549	0.19	6.8	175	0.7833	0.0254	5.7
Bottom 50 percentile	485	0.22	6.5	177	0.7761	0.0227	5.8
Top 50 percentile	443	0.25	6.3	182	0.7716	0.0213	5.8
Top 10 percentile	505	0.22	6.2	184	0.7810	0.0227	5.3
Top 5 percentile	535	0.21	6.2	182	0.7879	0.0243	5.3
Top 1 percentile	563	0.21	6.2	183	0.7987	0.0279	5.3
C. By market volatility (i.e., adjusted closing price of VIX) category							
Bottom 1 percentile	381	0.27%	9.5%	150	0.7928	0.0225%	5.6
Bottom 5 percentile	436	0.26	9.3	151	0.7975	0.0198	5.6
Bottom 10 percentile	460	0.25	8.5	157	0.7929	0.0195	5.5
Bottom 50 percentile	410	0.26	6.8	176	0.7735	0.0204	6.1
Top 50 percentile	518	0.21	6.1	184	0.7743	0.0235	5.5
Top 10 percentile	661	0.16	6.7	176	0.7896	0.0247	5.1
Top 5 percentile	740	0.15	7.3	167	0.8099	0.0253	5.0
Top 1 percentile	929	0.12	8.7	156	0.8205	0.0294	5.6

Notes: The time-series means of daily values are reported. Appendix A contains variable definitions and sample details.

percentage odd-lot volume was lower for the ETFs with higher AUM, indicating lower AT for large ETFs. Trade size was lower for ETFs with higher AUM. ETFs with higher AUM were more fragmented, as indicated by higher order fragmentation. ETFs with lower AUM had greater deviations from NAV and higher persistence.

Panel B of Table 4 shows these variables by the volatility rank of the ETFs. We found that the cancel rate was lower, the trade-to-order ratio was higher, and order fragmentation was generally higher for the ETFs with higher volatility. This finding indicates that the high-volatility ETFs have less algorithmic trading. We found a higher percentage odd-lot volume and lower trade size, however, for the ETFs with high volatility. ETFs with higher volatility had more deviations from NAV. We found no clear pattern in the persistence of those deviations.

Table 4. Algorithmic Trading, ETF Deviation, and Persistence of Deviation by ETF Characteristics, 2012–2018

	Cancel Rate	Trade-to-Order Ratio	% Odd-Lot Volume	Trade Size	Order Fragmentation	Absolute Deviation from NAV	Persistence of Deviation
A. By ETF AUM rank							
1 (lowest)	2,896	0.03%	9.4%	199	0.6862	0.0510%	13.0
2	2,197	0.05	8.7	198	0.7226	0.0401	11.9
3	1,164	0.08	8.4	189	0.7463	0.0314	10.1
4 (highest)	289	0.26	6.0	178	0.7799	0.0199	5.0
B. By ETF volatility rank							
1 (lowest)	884	0.18%	6.4%	203	0.7631	0.0223%	6.6
2	455	0.21	5.9	181	0.7759	0.0200	5.8
3	455	0.23	6.8	173	0.7747	0.0223	6.0
4 (highest)	429	0.32	7.6	174	0.7682	0.0286	5.8
C. By ETF turnover rank							
1 (lowest)	2,108	0.02%	12.0%	135	0.7389	0.0309%	9.7
2	644	0.08	8.6	157	0.7605	0.0219	6.9
3	346	0.17	6.2	174	0.7745	0.0206	5.8
4 (highest)	183	0.46	4.0	214	0.7906	0.0223	4.4
D. By ETF age							
0–5 years	774	0.12%	4.7%	254	0.7716	0.0308%	8.4
6–10 years	630	0.15	6.8	188	0.7623	0.0242	7.2
11–15 years	386	0.24	6.9	162	0.7851	0.0199	4.9
16–20 years	243	0.57	4.3	209	0.8090	0.0171	4.1

Notes: Time-series means of daily values are reported. Appendix A contains variable definitions and sample details.

In Panel C of Table 4, we present these variables by turnover rank of the ETFs. ETFs with high turnover had lower cancel rates, higher trade-to-order ratios, a lower percentage odd-lot volume, and larger trade sizes. These results indicate less algorithmic trading for ETFs with high turnover. Order fragmentation was also higher for ETFs with high turnover. We did not find any clear pattern for deviation from NAV. The persistence of deviations was lower for ETFs with high turnover.

Panel D of Table 4 shows these variables by age of the ETFs. The older ETFs had lower cancel rates and higher trade-to-order ratios, indicating less algorithmic trading for the older ETFs. No clear pattern is visible for percentage odd-lot volume, trade size, and order fragmentation by age group. Deviations from NAV, as well as persistence of those deviations, were lower for older ETFs. The deviation is 1.71 bps for the ETFs that had been around for 16–20 years, compared with 3.08 bps for the ETFs that were launched in the last 5 years.

Effect of AT on Deviation from NAV and Persistence of Deviations. We tested the effect of algorithmic trading on NAV deviation and persistence of deviations by using a regression framework. Following Jain et al. (2017), we used various cutoffs to identify high-frequency algorithmic trading. To create a dummy variable to capture high-frequency AT in ETFs, we first sorted all ETF-exchange days by trade volume and kept the top 50% as the ETF-exchange days group with high volume. We further sorted these ETF-exchange days by the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size to create quartiles. We then defined a dummy variable AT for each ETF-day that took the value of 1 only if an ETF was in the highest cancel-rate quartile or the highest percentage odd-lot volume quartile (or the lowest trade-to-order ratio quartile or the lowest trade-size quartile) and was in the top 50% of ETF-exchange days by volume. The value of this AT variable was zero for ETF-days that were in the bottom 50% by volume on all exchanges. Using a cutoff of 50% is consistent with the SEC's estimate of the share of high-frequency trading in the US market (SEC 2010). Our proxy enabled us to focus on a subset of stock exchange days that were most likely represented by high-speed algorithmic trades.[8]

Panel A of **Table 5** has results for the regression of deviations from NAV on algorithmic trading. We report standardized coefficients with *t*-statistics for all regression models.[9] The coefficients on AT are negative and statistically significant in all the models except Model 4. This finding indicates that the ETFs with higher AT had lower deviations from NAV. Thus, AT helps bring ETF prices in line with the underlying stocks' prices. Because the sum of daily trades/cancels/orders/odd-lot trades was used to calculate AT but NAV deviation was calculated at the end of the day, the results reflect the cumulative efforts of AT on an intraday basis to reduce NAV deviation. Following Piccotti (2018), we added variables to control for illiquidity, size, volatility, and age. The negative coefficients on log(AUM) indicate that deviation from NAV was less for the large ETFs, which are tracked and traded more actively than small ETFs. The positive coefficients on volatility indicate that higher volatility causes deviations from NAV to be greater. This finding is consistent with Piccotti, who found that volatility increases trading costs, making replication processes noisier. The negative coefficients on age indicate that deviations from NAV are fewer for the older ETFs.

Panel B of Table 5 provides results for the regression of persistence of deviations on algorithmic trading. The coefficients on AT are negative and statistically significant in all the models, which indicates that the ETFs with higher AT have a lower persistence of deviation. The negative coefficients on log(AUM) indicate that the persistence of those deviations is lower for large ETFs. The negative coefficients on volatility indicate that as price fluctuations increase, a particular run of premium or discount might not last long because the run may keep switching from premium to discount and vice versa. The negative coefficients on age indicate that the persistence of ETF deviations is lower for the older ETFs.

Double-Sort Analysis Based on AT and Spread. We performed a double-sort analysis on algorithmic trading and spread. We conjectured that some algorithmic traders use arbitrage strategies to profit from NAV deviations and bring ETF prices closer to underlying NAVs. Thus, the deviation from NAV and its persistence would be reduced by increased AT activity. The deviation from NAV (and its persistence) may also narrow (be shortened) when another type of algorithmic trader plays the role of market maker by posting narrower spreads. The resulting decrease in transaction costs of ETFs should further facilitate arbitragers' activity. NAV deviation provides an opportunity for traders to profit through arbitrage. Traders can buy ETFs trading at discounts and short the underlying securities. Conversely, they can short ETFs trading at premiums and buy the underlying securities. AT can reduce the NAV deviation through this channel of statistical arbitrage. For example, if an ETF has an NAV of $20.00 but is trading at $19.90, a trader can buy the ETF and short the underlying security. Box, Davis, Evans, and Lynch (forthcoming) found that bid and ask prices of ETFs and underlying securities converge in the minutes following such a mispricing event. Marshall, Nguyen, and Visaltanachoti (2013) found that a mispricing large enough to generate profit occurs on days when the spread is high. High spreads can deter statistical arbitrage. For example, if an ETF has an NAV of $20.00 and has a quote of $19.90–$20.00 (and a quote midpoint of $19.95), profiting from arbitrage may be difficult because a trader demanding liquidity has to place a marketable limit order (or market order) to buy it at $20.00. If the spread narrows and the quotes in this example change to $19.94–$19.96, a trader can buy the ETF at $19.96, short the underlying security, and book a profit. Thus, a lower spread can make it easier for a trader to take advantage of the arbitrage opportunity.

For these tests, we used the same definition of algorithmic trading, based on the cancel rate, as defined in the Table 5.[10] For each AT category based on the cancel rate, we created three groups based on spread. We then calculated the cross-sectional value-weighted or equal-weighted average of each group's deviation from NAV. We report the time-series

Table 5. Absolute Deviation from NAV and Persistence of Deviation: Regression on AT Dummy Variables, 2012–2018 (*t*-statistics in parentheses)

Variable	Cancel Rate (1)	Trade-to-Order Ratio (2)	% Odd-Lot Volume (3)	Trade Size (4)
A. Deviation from NAV				
Intercept	0.0000**	0.0000**	0.0000**	0.0000**
	(10.06)	(10.01)	(10.00)	(10.06)
AT	−0.0591**	−0.0438**	−0.0205**	−0.0039
	(−11.93)	(−9.67)	(−5.72)	(−1.31)
Spread	0.1347	0.1361	0.1382	0.1389
	(1.94)	(1.94)	(1.94)	(1.94)
Log(AUM)	−0.2022**	−0.2046**	−0.2115**	−0.2198**
	(−7.57)	(−7.60)	(−7.71)	(−7.86)
Volatility	0.0676**	0.0658**	0.0644**	0.0632**
	(14.94)	(14.71)	(14.42)	(14.21)
Age	−0.0671**	−0.0711**	−0.0662**	−0.0662**
	(−24.58)	(−23.81)	(−24.38)	(−24.59)
Adjusted R^2	0.1268	0.1254	0.1241	0.1238
Number of observations	487,326	487,326	487,326	487,326
B. Persistence of deviation				
Intercept	0.0000**	0.0000**	0.0000**	0.0000**
	(77.41)	(73.96)	(72.34)	(70.11)
AT	−0.0322**	−0.0145**	−0.0182**	−0.0254**
	(−18.76)	(−7.89)	(−9.97)	(−14.58)
Spread	0.0085	0.0099	0.0101	0.0100
	(1.86)	(1.88)	(1.88)	(1.89)
Log(AUM)	−0.1313**	−0.1363**	−0.1329**	−0.1296**
	(−43.48)	(−43.41)	(−41.60)	(−39.57)
Volatility	−0.0480**	−0.0496**	−0.0491**	−0.0484**
	(−21.59)	(−22.27)	(−22.00)	(−21.62)
Age	−0.0494**	−0.0506**	−0.0490**	−0.0483**
	(−22.99)	(−23.88)	(−22.79)	(−22.37)
Adjusted R^2	0.0358	0.0351	0.0351	0.0354
Number of observations	487,326	487,326	487,326	487,326

Notes: Appendix A contains variable definitions and sample details. All coefficients were standardized (standardized variables have zero mean and unit variance). The *t*-statistics, following Petersen (2009), are based on time-clustered standard errors.

**Significant at the 1% level.

means of those cross-sectional averages for each spread and AT category in Panel A of **Table 6**.

Table 6 shows that when we used value-weighted means, the differences between the deviation from NAV for ETFs experiencing high algorithmic trading and that of ETFs with low AT are negative and significant for the medium- and high-spread categories. The differences are negative and significant for all categories of spread when we used equal-weighted means. These results indicate that even after controlling for spread, AT plays a significant role in reducing deviations from NAV. With each AT category in Table 6, the difference between deviation from NAV for high-spread ETFs and deviation from NAV for low-spread ETFs is positive and significant, suggesting that transaction costs are an impediment to price efficiency.

We performed a similar analysis for the persistence of deviation and report those results in Panel B of Table 6. Overall, our results are consistent with the notion that AT reduces the persistence of deviations.

Mediation Analysis. Next, we performed a mediation analysis to test the arbitrage and market-making effects of algorithmic trading on deviations from NAV and their persistence. We report the results of this analysis in **Table 7**. We ran three regression models. We first regressed deviation from NAV on AT and spread (and other control variables). We then ran a similar regression by excluding spread. The purpose of our third regression was to examine the effect of AT on spread. Our results from these three regressions indicate that AT reduces deviation from NAV directly as well as indirectly through reduced spreads. The direct effect and total effect of AT on deviation from NAV, as well as the proportion of total effect mediated by spread, are reported in Table 7. Note that the percentage of indirect effect mediated by the spread is 13.62%. We also ran Sobel tests to confirm the significance of the mediation effect and found the *p*-value to be significant at the 1% level.[11]

We performed a similar mediation analysis for the persistence of the deviation. As Table 7 shows, we found that algorithmic trading reduces persistence of deviations directly as well as indirectly through reduced spreads. These mediation effects are statistically significant at the 1% level. The magnitude of the mediation effect is much smaller, however, for

Table 6. Double-Sort (by AT and Spread) Analysis, 2012–2018

	Value Weighted			Equal Weighted		
Variable	Low AT	High AT	Difference (high AT – low AT)	Low AT	High AT	Difference (high AT – low AT)
A. Deviation from NAV						
Low spread	0.0198	0.0196	−0.0002	0.0264	0.0224	−0.0040**
Medium spread	0.0321	0.0263	−0.0058**	0.0358	0.0302	−0.0056**
High spread	0.0515	0.0461	−0.0054**	0.0530	0.0492	−0.0038**
Difference (high spread – low spread)	0.0317**	0.0265**		0.0265**	0.0268**	
B. Persistence of deviation						
Low spread	4.8966	5.0107	0.1141*	7.0253	6.2503	−0.7750**
Medium spread	9.9195	8.7207	−1.1988**	11.3125	9.8542	−1.4583**
High spread	13.3147	12.8359	−0.4788**	13.2642	13.0169	−0.2473
Difference (high spread – low spread)	8.4181**	7.8252**		6.2389**	6.7666**	

*Significant at the 5% level.

**Significant at the 1% level.

Table 7. Mediation Analysis, 2012–2018

Variable	Direct Effect of AT	Total Effect (direct + indirect) of AT	Proportion of Total Effect Mediated	Sobel Test of Significance Level
Deviation from NAV	–0.0591**	–0.0685**	0.13616	**
Persistence of deviation	–0.0322**	–0.0328**	0.01787	**

Notes: The mediation analysis tested for direct and indirect effects (through reduced spread) of AT on deviation and persistence of deviation. Regression coefficients are standardized, and their statistical significance is based on time-clustered standard errors (see Petersen 2009).

**Significant at the 1% level.

the persistence of deviations. This result is consistent with the fact that spread mainly affects intraday arbitrage. Persistence of deviations is determined primarily by arbitrage by APs at the end of day and, therefore, is less affected by spread than are deviations from NAV.

Robustness Tests. We performed a series of robustness tests and report the results of some of them here. For our first robustness test, we modified the algorithmic trading dummies used in Table 5. We kept all ETF-exchange days (instead of eliminating the 50% of ETF-exchange days with low volume). We created quartiles based on daily values of the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size. We then defined a dummy variable AT for each ETF-exchange day that took a value of 1 if an ETF-exchange day fell in the highest cancel-rate quartile or the highest quartile based on percentage odd-lot volume (or the quartile with the lowest trade-to-order ratio or the lowest trade-size quartile). We found results (not reported for brevity) similar to those reported in Table 5.

For our second robustness test, we used the actual cancel rate, trade-to-order ratio, percentage odd-lot volume, and trade size variables as independent variables instead of dummy variables. Because most of the trading for ETFs happens on NYSE Arca, BATS-Z, Edge-X, and Nasdaq, we used the volume-weighted cancel rate, trade-to-order ratio, percentage odd-lot volume, or trade size from these four exchanges only for this analysis. We found that more algorithmic trading (i.e., a higher cancel rate, a lower trade-to-order ratio, higher percentage odd-lot volume, or lower trade size) resulted in fewer deviations from NAV. We also found that high AT resulted in low persistence of those deviations except when we used percentage odd-lot volume for the AT proxy. For brevity, these results, which are generally consistent with the findings in Table 5, are not reported here but can be found in the Supplemental Online Material.

For our third robustness test, we also used the cancel rate, the trade-to-order ratio, percentage odd-lot volume, and trade size on all exchanges without weighting by volume (unlike volume-weighted data in the second robustness test). We found (unreported) results similar to those in Table 5 except for the relationship between the trade-to-order ratio and persistence of deviation.

Our fourth robustness test followed Madhavan (2012) and involved using order fragmentation as a proxy for algorithmic trading in addition to the four proxies for algorithmic trading used in Weller (2018). We report these results in the Supplemental Online Material. We found that greater order fragmentation indicated higher AT. A negative coefficient on order fragmentation indicated that the absolute deviation from NAV and persistence of deviation were both lower for ETFs with high AT. The signs and significance of other control variables were the same as those reported in Table 5.

For our last robustness test, we kept only those ETFs in our sample that had traded every day since their inception and had at least one lit trade for each day in our sample. Using the sample of only 200 such ETFs, we ran tests similar to those reported in Panels A and B of Table 5 and found qualitatively similar (unreported) results.

All these robustness tests confirmed (with few exceptions) that algorithmic trading reduces deviations from NAV and the persistence of those deviations, thus increasing the efficiency of ETF prices. We found our main findings to be robust to sample selection and alternative measures of AT.

Conclusion

As investors continue to pour trillions of dollars into exchange-traded funds, understanding the mechanisms of ETF price efficiency and the impact of various market participants on it becomes ever more critical. Specifically, scrutiny of high-frequency algorithmic traders, who now represent a substantial portion of the stock market, has become more and more important. Regulators have voiced concern that high-frequency algorithmic trading may create price pressure on ETFs and exacerbate market disruptions. We showed in this article that high-frequency algorithmic traders play a productive and essential role in ETF price efficiency through arbitrage mechanisms that keep ETF prices aligned with their underlying assets' values.

We believe our study is the first to provide empirical evidence on the role of high-frequency algorithmic trading in ETFs. Using SEC MIDAS data compiled for 2012–2018, we found that high-frequency AT is prevalent in ETFs. Furthermore, we showed that high-frequency AT reduces the magnitude and persistence of ETF price deviations from NAV. This result was consistently found when multiple proxies of high-frequency AT were used. Our analyses showed that high-frequency AT reduces ETF price deviations from NAV directly and indirectly through reduced spreads. Our findings support and echo the notion that the flourishing of ETFs is partly the result of the active participation of high-frequency algorithmic traders (Merk 2014). The current system that Aldridge (2016) called the "HFT–ETF ecosystem" (with HFT standing for high-frequency trading) has worked well in preventing large price deviations that can propagate shocks and lead to market-wide instability.

Our study has two main practical implications for investors and regulators. First, although investors should still be aware of potential costs from ETF mispricing, investors can have confidence that in the presence of high-frequency trading, the ETF price is close to NAV. APs and their primary market transactions are known to keep ETF prices efficient, but we found that high-frequency algorithmic trading also plays a significant role—perhaps an even more important role than APs—in maintaining ETF price efficiency through intraday arbitrage. For institutional investors that trade heavily in ETFs, examining the prevalence of high-frequency AT in their ETFs can provide useful information for evaluating the efficiency of ETF prices and can mitigate mispricing costs.

Second, we have added to the continued debate over the controversial role of high-frequency algorithmic trading. Regulators and the investor community often highlight the potential negative impact of high-frequency AT in various markets, but we showed that in the ETF market, high-frequency AT plays a positive and necessary role in promoting ETF price efficiency and market stability. Restrictions on high-frequency AT of ETFs could increase market volatility and the mispricing risk for investors.

Appendix A. Variable Definitions and Data Description

Variable Definitions

Absolute deviation from NAV = absolute difference between the ETF quote midpoint and NAV of ETF, divided by the quote midpoint, and multiplied by 100. If the premium or discount is more than 10% greater than NAV, then the deviation is calculated as the absolute difference between the price and NAV, divided by price, and multiplied by 100.

Age = calendar year minus the year of ETF inception.

Algorithmic trading (AT) = following Jain et al. (2017), the main definition of AT here is as follows: All ETF-exchange days were sorted by trade volume, and the top 50% were kept to eliminate ETF-exchange days with low volume. The retained ETF-exchange days were sorted by the cancel rate (or trade-to-order ratio) to create quartiles. A dummy variable AT was assigned to each ETF-day that took a value of 1 if the ETF was in the quartile of highest cancel rates (lowest trade-to-order ratios) on any exchange.

Assets under management (AUM) = price times shares outstanding.

Cancels = number of orders canceled before execution.

Cancel rate = cancels divided by lit trades. A higher cancel rate indicates more algorithmic trading.

Discount to NAV = deviation from NAV for ETFs traded at a discount.

Lit trades = number of all trade messages for trades that are not against hidden orders.

Order fragmentation = 1 minus the Herfindahl–Hirschman Index of order volume across all the exchanges. The HHI ranges from 0 to 1, with higher figures indicating less fragmentation in that particular ETF. The fragmentation index and 1 minus the HHI are used here for clear interpretation. High order fragmentation indicates higher AT.

Order volume = volume of total orders placed.

Percentage odd-lot volume (% odd-lot volume) = volume of odd-lot trades divided by total trading volume, times 100, where odd-lot trades are defined as trades of less than 100 shares. A higher percentage odd-lot volume indicates more algorithmic trading.

Persistence of deviation = number of days in each run of deviation between an ETF's NAV and price.

Persistence of discount = number of days in each run when an ETF traded at a discount.

Persistence of premium = number of days in each run when an ETF traded at a premium.

Premium to NAV = deviation from NAV for ETFs traded at a premium.

Raw deviation from NAV = absolute difference between the quote midpoint and the ETF NAV, divided by the quote midpoint, and multiplied by 100.

Spread = ask price minus bid price divided by closing price.

Trade size = lit trade volume divided by lit trades. A lower trade size indicates more algorithmic trading.

Trade-to-order ratio = trade volume divided by order volume times 100. A lower trade-to-order ratio indicates more algorithmic trading.

Trade volume = number of shares traded.

Turnover = trade volume divided by shares outstanding.

Volatility = difference between high price and low price divided by high price.

Volatility = the highest ask minus the lowest bid divided by the highest ask price.

Data and Sample

The SEC provided the data on cancellations, trades, order volume, and trade volume for 13 US exchanges. Our sample period is January 2012 through June 2018. Data for closing prices, high prices, low prices, closing ask prices, closing bid prices, and shares outstanding are from CRSP. The list of US equity ETFs (excluding leveraged and inverse ETFs) for our sample came from ETFdb.com—662 such ETFs in December 2018. The NAV data came from Bloomberg, and we merged those data with the SEC data.

The intersection of CRSP data, SEC data, and ETF data resulted in 633 ETFs. We eliminated from our sample ETFs that had no more than one lit trade. We removed ETF-days with ETF premiums/discounts greater than 20%. **Table A1** summarizes ETFs dropped at each stage. These steps resulted in a sample of 623 ETFs. Then, we trimmed all the variables at the 1st and 99th percentiles. The result was a final sample of 578 ETFs.

Table A1. Formation of Final Sample

Total ETFs downloaded from ETFdb.com (US equity, not leveraged, not inverse)	662
– ETFs not found in CRSP/Compustat	–29
– ETFs with only 1 or 0 lit trades	–9
– ETF with premiums/discounts greater than 20% on all ETF-days	–1
– ETFs with only outlier variable values identified by trimming the variables at 1st and 99th percentiles	–45
Final ETF sample	578

Notes: On 8 April 2020, ETFdb.com listed 2,294 ETFs in total, of which 1,543 were equity ETFs and 950 were US equity ETFs. Excluding leveraged and inverse funds left 835 ETFs.

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Notes

1. Algorithmic trading refers to the use of computer algorithms to automatically submit, update, and cancel orders (Hendershott, Jones, and Menkveld 2011). High-frequency algorithmic trading is a subset of algorithmic trading that involves the "use of extraordinarily high speed and sophisticated programs for generating, routing, and executing orders" (SEC 2010).

2. An AP is an organization that has the right to create and redeem shares of an ETF. APs provide a large portion of the liquidity in the ETF market by obtaining the underlying assets required to create the shares of an ETF.

3. Similar to Weller (2018), we used the cancel rate, the ratio of trading volume to order volume, percentage odd-lot volume, and trade size as proxies for algorithmic trading. Higher odd lots and cancel-to-trade ratios indicate more algorithmic trading. On the contrary, higher trade-to-order volume ratios and larger average trade sizes indicate less algorithmic trading.

4. When the premium/discount based on midpoint prices was more than 10 percentage points greater in absolute terms than the premium/discount based on prices, we followed Broman (2016) and used prices instead of midpoint quotes to calculate the deviation.

5. We also computed autocorrelations of the NAV deviation (unreported). We found the equal-weighted daily autocorrelation to be only 0.23 across all funds and the average half-life of the deviations to be 0.47 day.

6. Order fragmentation as an AT proxy in regression analysis is discussed only for the material on robustness checking in the Supplemental Online Material.

7. In untabulated results, we also examined how many exchanges an ETF was traded on in a given day. We found that 94% of the ETFs were traded on at least seven exchanges on a given day.

8. Results based on actual data for the four proxies of algorithmic trading are reported as a robustness check and can be found in the Supplemental Online Material.

9. Because error terms for deviations and persistence of deviations at a given point in time may be correlated as a result of market sentiment and availability of arbitrage capital, we used time-clustered standard errors.

10. The results are qualitatively similar when we used other AT proxies, such as the trade-to-order ratio, percentage odd-lot volume, and trade size; these results are not reported here for brevity.

11. For the Sobel tests, we used 1 – AT instead of AT as the independent variable because AT and spread have coefficients of opposite signs.

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