ETF Liquidity

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Abstract

We provide a comprehensive analysis of ETF liquidity based on tick and daily data for in excess of 800 ETFs over the 1996-2014 period. We make several contributions. First, we show there is a strong relation between ETF and underlying stock liquidity. ETF liquidity is influenced by and influences underlying stock liquidity. Second, both supply- and demand-side factors have a strong bearing on ETF liquidity. Third, the end-of-day spread, high-low, and Amihud proxies best measure actual transaction costs. Fourth, there are intraday and daily patterns in spreads. Finally, liquidity risk is priced in ETF returns.

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1. Introduction

Liquidity has received a lot of attention from researchers due to the critical role it plays in financial markets. Papers have documented for stocks, bonds, commodities, and currencies a) the level of transaction costs, b) how best to measure liquidity, c) variation in liquidity across different time periods, and d) the link between liquidity and returns.[1] However, there has been relatively little focus on exchange traded fund (hereafter ETF) liquidity despite the surge in ETF investment, the increased focus on ETFs from researchers, and the unique characteristics of ETFs. We provide a comprehensive examination of ETF liquidity using tick and daily data for over 800 ETFs.

There has been a sharp increase in the number, variety, and asset value of ETFs. While the original ETFs were backed by physical assets, many current ETFs now provide asset class exposure via derivative contracts. Early ETFs provided long-only equity market exposure but it is now possible to find ETFs with short and leveraged exposure to equity sectors, styles, bonds, commodities, currencies, real estate, and other "exotic" asset classes. The assets of U.S. listed ETFs are estimated to have grown to over US1.7 trillion by the beginning of 2014, with ETFs typically representing between 25% to 40% of the total dollar volume of trading on U.S. exchanges (e.g. Hill, Nadig, and Houhan, 2015).

There are several reasons why ETF liquidity may differ from the liquidity of other instruments such as stocks. First, Kyle (1985) and Admati and Pfleiderer (1988) show there can be a reluctance to supply liquidity when there are concerns that other market participants have superior information. Adverse selection costs are therefore an important aspect of

[1] These papers include a) Goyenko, Holden, and Trzcinka (2009), Edwards, Harris, and Piwowar (2007), Mancini, Ranaldo, and Wreampelmeyer (2013), and Marshall, Nguyen, and Visaltanachoti (2012), b) Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), Corwin and Schultz (2012), Chung and Zhang (2014), Marshall, Nguyen, and Visaltanachoti (2012), Karnaukh, Ranaldo, and Soderlind (2015), c) Chordia, Sarkar, and Subrahmanyam (2005), and d) Amihud and Mendelson, 1986), Acharya and Pedersen (2005), Bali, Peng, Shen, and Tang (2013).

liquidity and liquidity proxies (e.g. Glosten, 1987). However, Subrahmanyam (1991) posits that a basket of securities (such as an ETF) should have higher liquidity than the underlying stocks due to lower adverse selection costs. Second, Bessembinder, Carrion, Tuttle, and Venkataraman (2015) find that the liquidity of ETFs holding futures contracts is affected by the rolling of contracts. Spreads are lower and depth is higher on roll dates.

While it is well known that the first ETFs on large equity indices have extremely low bid-ask spreads (e.g. Hill, Nadig, and Hougan, 2015), the relatively large transaction costs of more exotic ETFs are also receiving attention.[2] Our first contribution is providing comprehensive measures of transaction costs across ETFs and through time. These will likely to be of interest to a number of parties. The first group are investors and researchers. Lesmond, Schill, and Zhou (2004) show transaction costs are a crucial input into analysis to determine whether active investment strategies add value, while De Roon, Nijman, and Werker (2001) find apparent diversification advantages often disappear when transaction costs are accounted for. The second group is risk managers. Elton, Gruber, Comer, and Li (2002) find ETFs are popular hedging tools and Perold and Schulman (1988) point out that transaction costs are a key input in judging hedging effectiveness. Transaction costs are also very relevant for exchanges, as Harris (2003) suggests they are an important determinant of the level of business they attract. Finally, Chordia, Roll, and Subrahmanyam (2008) show that there is a direct link between transaction costs and market efficiency so transaction costs affect all market participants.

Our sample includes US, international, market, style, and sector equity ETFs, and bond, commodity, currency, real estate, and “other” ETFs, which include those providing more exotic exposure, such as long – short positions. Our results show average effective spreads over the 1996 – 2014 period range from 0.187% for commodities to 0.572% for

[2] http://www.nasdaq.com/article/biggest-etf-myths-that-can-lead-to-investor-mistakes-cm345940

international equities. Some of the variation in spread across asset classes is accounted for by the different start dates and the trend of lower transaction costs through time. However, this is not the entire explanation. While there are many very liquid international equity ETFs, there are also a large number that are relatively illiquid. Overall, ETF transaction costs compare very favorably to the average developed and emerging market effective spreads of 2.2% and 2.7% documented by Fong, Holden, and Trzcinka (2010) for the 1996 – 2007 period.

Our second contribution is comparing the transaction costs of the most liquid Dow Jones Industrial Average (DIA) ETF to the transaction costs of the underlying stocks over time. Hedge and McDermott (2004) provide empirical evidence that transaction costs are lower for this ETF than for the basket of underlying securities over the fifty days following the launch of the ETF, and we add to their work by measuring transaction costs from inception in 1998 to 2014. The ETF effective spreads declined from 0.075% in the 1998 – 2005 period to 0.021% in the 2006 – 2014 period, while the underlying stock transaction costs declined from 0.083% to 0.023% over the same two periods. The fact that ETF transaction costs are lower in both periods and in the overall sample confirms Subrahmanyam's (1991) suggestion that ETFs should have higher liquidity than the underlying stocks due to lower adverse selection costs. Movements in underlying stock liquidity influence future ETF liquidity, and while there is evidence of ETF liquidity also influencing underlying asset liquidity, this relation is weaker.

Measuring market wide liquidity can be computationally intensive, particularly if intraday data is being used. ETF liquidity is an attractive substitute since the liquidity of a singular series can be measured. For instance, Chiu, Chung, Ho, and Wang (2012) investigate funding and equity liquidity during the subprime crisis period using ETFs. However, while ETF prices and returns typically do a good job of tracking prices and returns in the underlying instruments (particularly long-only liquid ETFs), as noted by Elton, Gruber, Comer, and Li (2002), we are not aware of any paper that documents the relation between changes in liquidity levels across ETFs and underlying securities. This is the third contribution of this paper. We find that the correlation between ETF and underlying transaction costs is 0.80 over the 1998 to 2014 period. This has declined in the most recent sub period, but it appears that movements in ETF liquidity remain a reasonably proxy for movements in the liquidity of stocks in the ETF. Changes in both the TED spread, which may be thought of as a supply-side factor, and the VIX, which is a proxy for demand-side factors explain ETF and underlying stock liquidity. However, their relationship with ETF liquidity is stronger. Moreover, the strong impact of market volatility on ETF liquidity is not limited to the "Flash Crash" period.

The lower adverse selection costs in ETFs raises a question regarding the effectiveness of liquidity proxies, which have been typically developed for individual stocks, for ETFs. Addressing this question is the fourth contribution of this paper. There have been important advances in the liquidity proxy literature in recent times, with studies establishing proxies that provide accurate measures of the actual cost of trading. Equity market tests include: Goyenko, Holden, and Trzcinka (2009) who find the Effective Tick proxy best measures effective and realized spread transaction costs, while Amihud (2002) best represents price impact; Hasbrouck (2009) who shows a Gibbs based estimate is an effective proxy; Corwin and Schultz (2012) who develop a spread estimator based on high-low prices; Chung and Zhang (2014) who show daily bid-ask spreads can be effective measures. Marshall, Nguyen, and Visaltanachoti (2012) find the Amihud proxy performs the best in commodities, with Effective Tick and Amivest measures also performing well. Karnaukh, Ranaldo, and Soderlind (2015) show the Corwin and Schultz (2012) and daily bid-ask spread measures work best in currencies.

We find the Roll, Effective Tick, Fong, Holden, and Trzcinka (FHT), Daily Spread, High-Low, Amihud, and Amivest measures all do a good job of being a proxy for the effective spread and quoted spread benchmarks. However, the Daily Spread and High-Low prove to be the best measures to use. A number of proxies also do a good job at capturing movements in price impact, with Amihud and a Daily Spread Impact measure being the best performers.

All types of market participants have an incentive to execute their orders in a way that minimizes transaction costs. As such, it is important investors have an understanding of any variation in transaction costs within the day or across days or months. It is also useful for researchers to understand liquidity patterns. For instance, if transaction costs are typically larger at the end of the day, then using end-of-day spreads may overstate the transaction costs investors can achieve and thereby understate the net returns to an investment approach. Chordia, Sarkar, and Subrahmanyam (2005) find both stock and bond market liquidity is higher at the beginning of the week and lower on a Friday. Moreover, liquidity is higher in July through September than the rest of the year. There is also a well-documented pattern in intraday stock liquidity with bid-ask spreads higher at the market open and close than the middle of the trading day (e.g. McInish and Wood, 1992). Our fifth contribution is investigating seasonal patterns in ETF liquidity. There is evidence that spreads are higher following a period of no trading, such as on a Monday, due to increased adverse selection costs. The Foster and Viswanathan's (1990) theoretical model suggests the adverse selection component of the bid-ask spread will be largest on a Monday due to the arrival of information over the weekend when trading cannot take place.

However, there are questions around whether these patterns driven by adverse selection costs will apply in ETFs given the evidence that adverse selection is much lower in these products. ETFs also have other unique characteristics. For instance, unlike stocks, many

ETFs can be created and redeemed on a daily basis by investors who supply or wish to receive the underlying securities.

We find evidence of an intraday pattern in liquidity with effective spreads higher in the first half hour of trading than at other points of the day in each group of ETFs. While there is some indication of lower spreads at the end of the day, this result is not consistent across all ETF groups. In contrast to the equity literature, we do not find ETF spreads are consistently larger on Mondays than other days of the week. There is some evidence of larger spreads on Mondays than other days for some ETFs but this does not apply universally. There does however appear to be a quarterly effect. Spreads are larger in the fourth quarter than other quarters in the majority of ETFs.

It is well documented that investors should demand higher expected returns for holding less liquid stocks (e.g. Amihud and Mendelson, 1986). Moreover, Acharya and Pedersen (2005) point out that a persistent negative liquidity shock should result in low contemporaneous returns and high future returns. However, as Bali, Peng, Shen, and Tang (2013) note, there may not be a negative relation between liquidity and future returns due to market frictions, such as illiquidity and investor inattention. Our sixth contribution is studying the link between liquidity shocks and returns in ETFs. This is a timely examination as Borkovec, Domowitz, Serbin, and Yegerman (2010) find the 2010 "Flash Crash" affected ETFs much more severely than stocks. They suggest the failure of price discovery in many ETFs was likely caused by a huge decline in liquidity. More recently, Newman (2015) notes that on August 24, 2015 the S&P 500 index fell by around 6%, but an equal weight S&P 500 ETF dropped by over 34%, which is many times more than the equal weight decline in the underlying stocks. Newman (2015) suggests that one reason for this may be the large proportion of market orders by individual investors in ETFs.

We find liquidity declines result in lower contemporaneous ETFs returns in eight of the ten ETF groupings. Moreover, the results indicate the shock is reflected in returns much more quickly than it is in equities. We find no relation between a liquidity shock and subsequent equity returns when the effective spread is used as the liquidity proxy, while the relation is statistically significant in most but not all the ETF groupings when quoted spread is the liquidity proxy. A possible explanation for the faster reaction in ETFs is the lower transaction costs and reduced liquidity frictions in ETFs compared to stocks.

The ETFs in our sample track a diverse range of underlying assets and start at different points in time, with equity, real estate, commodity, bond, currency, and "other" ETFs commencing in 1996, 2000, 2001, 2002, 2005, and 2006 respectively. However, our core results are remarkably consistent across ETFs. This indicates that conclusions can be drawn about ETF liquidity in general rather than for some but not all ETFs. It also suggests that any changes to market liquidity over time from events such as decimalization, algorithmic trading, exchange mergers, and the global financial crisis do not materially affect our results.

The rest of this paper is structured as follow. Section 2 contains the data. The method and results are in Section 3, and Section 4 concludes the paper.

2. Data

We source daily price, volume, and shares outstanding data from CRSP, and intraday data from Thomson Reuters Tick History (TRTH). These data, which are provided to us by the Securities Industry Research Centre of Asia Pacific (SIRCA), are used by central banks, regulators, hedge funds, investment banks, and researchers such as Marshall, Nguyen, and Visaltanachoti (2012) and Hendershott and Riordan (2013).

We include all ETFs that appear in both data sets between January 1, 1996 and December 31 2009. Our data ends on 31 December 2014 so we do not include ETFs listed in recent years due to concerns around insufficient time series length for meaningful liquidity proxy correlation analysis.

We assign ETFs to categories based on http://etfdb.com/. The final data set includes 870 ETFs, including 571 equity, 83 bond, 17 commodity, 19 currency, 25 real estate ETFs. If an ETF provides leveraged or short exposure to any of these asset classes we classify it as “other”. There are 155 ETFs in this category. The equity ETFs include 411 tracking U.S. indices and 160 following international indices. There are 97 providing aggregate market exposure, 266 offering sector exposure, and 208 giving a particular style such as value or growth. As shown in Appendix 1, the number of ETFs has grown through time, from 19 in 1996 to 643 in 2014. Hill, Nadig, and Houhan (2015) note there was a sharp increase in the number of ETFs providing exposure to assets other than equities around the time the global financial crisis was having major impact on equity returns. The number of “other” ETFs, which include more exotic exposure such as long-short positions, illustrates this, with our sample increasing from 14 ETFs in 2006 to 126 in 2008. Some ETFs appear in our sample for a period and then drop out due to either the ETF ceasing to exist or incomplete data. However, there is no evidence that this has any impact on our results. ETFs that attract less interest than expected are likely to be those most likely to cease to exist, but we our results are very similar across ETFs with different levels of liquidity, rather than just applying to more liquid ETFs.

3. Method and Results

3.1. ETF Transaction Costs

We use three transaction cost benchmarks. These are effective spread, quoted spread, and price impact.[3] We calculate effective spread as per equation 1:

$$\text{Effective Spread} = 2 \cdot |\ \ln(P_k) - \ln(M_k)|, \qquad (1)$$

where P_k is the price and M_k is the midpoint of the bid and ask quotes when kth trade occurs. Following Goyenko, Holden, and Trzcinka (2009), we calculate monthly average effective spreads by weighting intraday spreads by dollar volume.

We calculate quoted spread as per equation 2:

$$\text{Quoted Spread} = (A_k - B_k)/M_k, \qquad (2)$$

where A_k , B_k , and M_k is the ask price, bid price, and midpoint of these two prices respectively. Following Fong, Holden, and Trzcinka (2011), the monthly average quoted spread is calculated by time weighting the intraday spreads.

We calculate the five-minute price impact as per equation 3:

$$\text{Price Impact } = \begin{cases} 2 \cdot \left(\ln(M_{k+5mins}) - \ln(M_k)\right) \text{ when the } k^{th} \text{ trade is a buy,} \\ 2 \cdot \left(\ln(M_k) - \ln(M_{k+5mins})\right) \text{ when the } k^{th} \text{ trade is a sell,} \end{cases} \qquad (3)$$

[3] We only calculate each benchmark in the market session in each country. Some exchanges have a pre-market and post-market session but these are not included to ensure consistency.

where $M_{k+5mins}$ (M_k) are the midpoints five minutes after (at the time of the kth trade). Again, we use the Lee and Ready (1991) algorithm to classify trades, and monthly averages are calculated using the same approach as for effective spreads.

In Table 1 we present mean transaction costs for the overall period and through time.[4] The Panel A results indicate commodity ETFs have the lowest effective spreads overall at 0.187%, followed by currency (0.196%), bond (0.20%), and US equity (0.271%) ETFs. International equity ETFs have the largest effective spreads at 0.572%. Of course, these are average numbers for all ETFs within a category. Many US stock ETFs, such as the S&P 500 SPDR and iShare ETFs have extremely low transaction costs. Transaction costs have declined through time, and the fact that ETFs have launched at different points makes conclusions more problematic, but the patterns in the most recent 2010 – 2014 sub-period are broadly consistent with those from the overall period.

Quoted spreads are typically larger than the equivalent effective spreads, but they generally follow the same pattern across different ETF categories. They range from 0.243% for commodity ETFs to 0.751% for international equity ETFs for the entire period and from 0.140% for commodity ETFs to 0.507% for other ETFs in the 2010 – 2014 sub-period. Price impact transaction costs are typically lower, and the order is slightly different. Equity ETFs providing exposure to a particular style have average costs of 0.119%, while other ETFs have an average price impact of 0.271%.

By way of comparison, Goyenko, Holden, and Trzcinka (2009) report average effective spreads of 2.6-2.9% for 400 randomly selected NYSE, Amex, and Nasdaq stocks over the 1993 – 2005 period. Corwin and Schultz (2012) find an average effective spread of 2.4% based on all NYSE, Amex, and Nasdaq stocks that meet their sample selection criteria

[4] The median results in Appendix 2 lead to very similar conclusions.

over the 1993 – 2006 period. Fong, Holden, and Trzcinka (2010) report average effective spreads of 2.2% and 2.7% respectively for developed and emerging markets over the 1996 – 2007 period. Mancini, Ranaldo, and Wrampelmeyer (2013) report average bid-ask spreads from 0.01-0.08% for nine liquid exchange rates over the 2007 – 2009 period. Marshall, Nguyen, and Visaltanachoti (2012) find median effective spreads of 0.16% for 24 commodity futures over the 1996 to 2009 period. They find considerable cross-sectional variation with the median cost for Brent Crude Oil of 0.04% compared to 0.42% for lead.[5]

[Insert Table 1 About Here]

3.2. ETF Versus Underlying Stock Liquidity

In this section, we present and discuss results relating to the liquidity of the Dow Jones Industrial Average Diamond ETF (DIA) versus the liquidity of the stocks that comprise the Dow Jones Industrial Average. It is well documented that adverse selection costs are an important aspect of transaction costs. Investors who are concerned that others may have an informational advantage regarding a stock are less likely to supply liquidity and bid-ask spreads will be larger as a result. This leads Subrahmanyam (1991) to suggest that instruments like ETFs should have lower transaction costs due to lower asymmetric information costs.

Hedge and McDermott (2004) present evidence to support the Subrahmanyam (1991) proposition over the fifty days following the launch of the DIA ETF, and we add to this work by considering transaction costs from the date the DIA ETF was launched in 1998 to 2014. We obtain tick data for the ETF and for the underlying stocks and then measure the daily

[5] We present additional results by size and liquidity quintile in Appendix 3.

ETF effective spread and the price-weighted effective spread of the stocks that comprise the DJIA.

We find ETF spreads are lower than the average underlying spread in the overall sample period and two sub periods. The ETF effective spreads declined from 0.075% in the 1998 – 2005 period to 0.021% in the 2006 – 2014 period, while the underlying stock transaction costs declined from 0.083% to 0.023% over the same two periods. Figure 1 reinforces the increased liquidity through time. It also highlights the sharp increase in spreads during periods of heightened volatility, such as the flash crash, which is consistent with Borkovec, Domowitz, Serbin, and Yegerman (2010). Our findings are also in accordance with Hamm (2014) who finds a positive relation between the percentage of firm shares held by an ETF and illiquidity in the underlying stock, suggesting that uniformed investors prefer transacting in the ETF.

We now turn our attention to the question of whether ETF liquidity can be used as a proxy for the liquidity of the underlying assets. Measuring the liquidity of a market or a large number of assets can be computationally intensive, especially if intraday data is being used. In contrast, ETF liquidity can be measured using a singular series, so if this represents underlying liquidity it is an attractive substitute. For instance, Chiu, Chung, Ho, and Wang (2012) use ETFs to investigate funding and equity liquidity during the subprime crisis period. There is a large literature which shows that ETFs, and in particular, long-only liquid ETFs do a good job of tracking price movements of the index they mirror (e.g. Elton, Gruber, Comer, and Li (2002)). However, there does not appear to be research that considers the relation between changes in liquidity levels across ETFs and underlying securities.

Over the 1998 to 2014 period we find that the correlation between ETF and underlying stock effective spreads is 0.803. This correlation has declined to 0.463 in the 2006 - 2014 sub-period, but this indicates researchers can still use movements in ETF liquidity to get an indication of the movements in the liquidity of the underlying assets. However, while this may be the case for ETFs that hold the physical assets that they track, it is not clear whether this would also apply to ETFs achieving exposure through synthetic instruments.

In Panel C we present daily Granger Causality analysis for ETF effective spreads and the weighted effective spreads of the underlying index. It seems reasonable to expect that liquidity from underlying assets will influence the liquidity of an ETF that holds these assets. Moreover, it is possible that ETF liquidity may influence the liquidity of the underlying assets. If there is increased interest in an ETF and liquidity improves, there may be the incentive for more ETF units to be created. The results indicate there is strong evidence that movements in the liquidity of the underlying DJIA stocks influence DIA ETF liquidity for up to ten days in the future. ETF liquidity also influences the liquidity of the underlying stocks but this influence is weaker.

In Figure 2 we show the impulse response function results for a shock in ETF liquidity and a shock in underlying stock liquidity. The four graphs in Figure 2 show the impact of a 1% increase in the effective spread of the ETF and underlying stocks on themselves and each other. The key message is that ETF liquidity is more sensitive to a shock in underlying liquidity than underlying liquidity is to a shock in ETF liquidity. The first graph (top left) shows the ETF takes approximately 12 days to fully absorb its own liquidity shock, while bottom right graph shows the underlying stocks take longer than 12 days to absorb their own liquidity shock. The liquidity shock impact from the ETF on the underlying (top right) increases to a maximum of 0.1% at day 4, before gradually declining and disappearing after day 12. By comparison, the response of ETF liquidity to a shock in underlying liquidity is much stronger. The increase reaches a peak of 0.6% at day 4 and the impact lasts longer than 12 days.

[Insert Table 2 About Here]

[Insert Figure 1 About Here]

[Insert Figure 2 About Here]

In Table 3 we investigate whether demand- or supply-side explanations explain ETF and underlying liquidity. Following Karnaukh, Ranaldo, and Soderlind (2015), we use change in VIX as a proxy for demand-side liquidity factors and change in the TED spread as a proxy for supply-side liquidity factors. We run daily regressions based on changes in the average daily effective spreads and also include the lag DJIA and lag spread changes as control variables. The results indicate strong evidence to support both demand- and supply-side explanations. Increases in VIX and the TED spread lead to more illiquidity in both the ETF and DJIA component stocks. However, the effect is stronger for ETFs. The statistical significance is consistently stronger for ETFs and the TED coefficient is over twice as large for the ETF compared to the underlying. The positive coefficient in the ETF minus underlying difference regression indicates that increases in VIX lead to a larger increase in ETF transaction costs.

[Insert Table 3 About Here]

3.3. Measuring ETF Liquidity Using Low Frequency Proxies

In this section we document the low frequency liquidity proxies, present correlations between these and the transaction cost benchmarks, and report Root Mean Squared Errors.

3.3.1. Low Frequency Proxy Measurement

The liquidity proxies we test include Roll (1984), Gibbs (from Hasbrouck, 2009), Zeros (from Lesmond, Ogden, and Trzcinka, 1999) Zero2 (from Goyenko, Holden, and Trzcinka, 2009), FHT (from Fong, Holden, and Trzcinka, 2011), Effective Tick (from Goyenko, Holden, and Trzcinka, 2009, and Holden, 2009), High-low (from Corwin and Schultz, 2012), Daily Spread (from Chung and Zhang, 2014), Amihud (2002), Amivest (from Amihud, Mendelson, and Lauterback, 1997), Pástor–Stambaugh (2003), and range of spread proxies converted price impact proxies by dividing by average daily dollar volume, as per Goyenko, Holden, and Trzcinka (2009).

We calculate the modified Roll (1984) effective spread estimator for each ETF each month, as per Goyenko, Holden, and Trzcinka (2009), as in equation 4:

$$\text{Roll} = \begin{cases} 2\sqrt{-Cov\left(\Delta P_t, \Delta P_{t-1}\right)} & \text{when } Cov\left(\Delta P_t, \Delta P_{t-1}\right) < 0 \\ 0 & \text{when } Cov\left(\Delta P_t, \Delta P_{t-1}\right) \geq 0 \end{cases} \quad (4)$$

We measure the Bayesian Gibbs sampling Roll (1984) model in accordance with Hasbrouck (2004, 2009) as in equation 5, where p_t, q_t, c, and $r_{m,t}$ is the log trade price, a trade indicator, the first autocovariance of price changes (half spread), and the market return factor respectively The variable priors and estimation procedure are as per Hasbrouck (2009).[6]

$$\Delta p_t = c\Delta q_t + \beta_m r_{m,t} + u_t \quad (5)$$

[6] We thank Joel Hasbrouck providing his code on his website: http://pages.stern.nyu.edu/~jhasbrou/Research/GibbsCurrent/Programs/RollGibbsLibrary02.sas.

The Zeros measure of Lesmond, Ogden, and Trzcinka (1999) and the modified "Zeros2" are given in equations 6 and 7, where T represents the total number of trading days in a month.

$$\text{Zeros} = (\text{\# of days with zero returns})/T \quad (6)$$

$$\text{Zeros2} = \left(\text{\# of positive-volume days with zero returns}\right)/T \quad (7)$$

The FHT proxy, which was developed by Fong, Holden, and Trzcinka (2010) is given in equation 8:

$$\text{FHT} = 2\sigma N^{-1}\left(\frac{1+z}{2}\right) \quad (8)$$

where σ is the standard deviation of the ETF's daily returns, and z, and $N^{-1}(\ )$ the proportion of zero returns, and the inverse of the cumulative normal function respectively.

Goyenko, Holden, and Trzcinka (2009) and Holden (2009) develop a number of spread measures that account for clustering in the price grid. We use the "Effective Tick" measure which probability weights each effective spread size and then divides by the average price in the time interval.

The Corwin and Schultz (2012) high – low price spread estimator is below:

$$S = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}}, \quad (9)$$

where:

$$\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3\text{-}2\sqrt{2}} - \sqrt{\frac{\gamma}{3\text{-}2\sqrt{2}}} \quad , \beta = \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}^{O}}{L_{t+j}^{O}}\right)\right]^2, \;\; \gamma = \left[\ln\left(\frac{H_{t,t+1}^{O}}{L_{t,t+1}^{O}}\right)\right]^2$$

where $H_{t,t+1}^{O}$ ($L_{t,t+1}^{O}$) are high (low) prices over the two days *t* and *t* + 1, respectively.

Chung and Zhang (2014) find the end-of-day spread calculated from CRSP data, as given in equation 10 is a reliable transaction cost proxy.

$$\text{Daily Spread} = (A_k - B_k)/M_k, \tag{10}$$

The Amihud (2002) proxy and closely related Amivest measure from Amihud, Mendelson, and Lauterback (1997) are given in equation 11 and 12 respectively.

$$\text{Amihud} = \frac{|r_t|}{Volume_t} \tag{11}$$

$$\text{Amivest} = \frac{Volume_t}{|r_t|} \tag{12}$$

where r_t is the return and $Volume_t$ is the dollar volume on day *t*.

The Pástor–Stambaugh (2003) or “gamma” liquidity measure is in equation 13:

$$r_{t+1}^{e} = \theta + \varphi r_t + \gamma sign(r_t^{e}) Volume_t + \varepsilon_t \tag{13}$$

where r_t is the stocks return and r_t^{e} is the excess return, r_t - r_{mt}, on day *t*. S*ign*(r_t^{e}) is one (zero) if r_t^{e} is positive (negative), and $Volume_t$ is the dollar volume on day *t*.

Consistent with Goyenko, Holden, and Trzcinka (2009) we convert the spread proxies to price impact proxies by dividing by average daily dollar volume.

3.3.2. Low Frequency Proxy and Transaction Cost Benchmark Means

In Table 4 Panel A, we present mean effective and quoted spreads alongside means for each of the spread proxies. These are based on the cross-sectional average for each class of ETF each month and then the average through time. As well as averages for each ETF category, we also classify all ETFs, regardless of their type into size and liquidity quintiles. The Zeros and Zeros2 proxies are not designed to be liquidity measures of a size that is similar in magnitude to the underlying transaction cost benchmarks, but the other proxies are.

The average effective and quoted spread measures across the different ETF groupings are 0.328 and 0.431 respectively. The closest proxy mean is for the high-low proxy (0.371), followed by 0.539 for the Daily Spread, 0.736 for Roll, and 0.873 for Gibbs. The FHT and Effective Tick means are, at 0.068 and 0.034, considerably smaller than the benchmark means. We test whether the differences between the liquidity proxy levels and benchmarks are statistically significant using Root Mean Squared Error analysis and report the results in Section 3.3.4.

[Insert Table 4 About Here]

3.3.3. Correlations

In Table 5 we present spearman correlation coefficients between the spread proxies, and, following Goyenko, Holden, and Trzcinka (2009), the Amihud and Amivest proxies, versus the effective spread benchmark. These correlations are based on the time-series method (monthly cross-sectional averages are calculated and time series correlations are calculated through time), but cross-sectional correlations which generate similar results are available on request. Correlations that are statistically significant at the 10% level or more are in bold and those that are statistically significant and also of the correct sign have a box around them.

The results indicate the Roll, Fong, Holden, and Trzcinka (FHT), Effective Tick, Daily Spread, High-Low, Amihud, and Amivest measures all do a good job of measuring movements in the effective spread. Of the 20 ways we use to divide up the ETF universe, we find statistically significant correlations (of the correct sign) in all 20 subsets for the Roll, FHT, Daily Spread, and High-Low proxies. Nineteen of the 20 correlations are statistically significant for Amihud and Effective Tick. Amivest exhibits eighteen significant correlations. The Gibbs, Zeros and Zeros2 measures appear to do a good job of tracking liquidity on the size and liquidity quintile portfolios. However, neither of these proxies consistently has positive statistically significant correlations in the ETF groupings based on the asset classes they represent.

Turning to the average correlations, it is evident Daily Spread, High-Low, and Amihud have the largest absolute values at 0.841, 0.746, 0.614, respectively. While Roll and FHT proxies produce consistent statistically significant correlations across all 20 series, their average correlations are somewhat lower at 0.526 and 0.446 respectively. Moreover, the Effective Tick average correlation is 0.491 and Amivest is -0.399. There is no pattern of proxies all being more effective on one type of ETF than the others. For instance, the largest correlation for the High-Low measure is 0.907 for currencies, while largest correlation for the Daily Spread measure is 0.95 equity market ETFs. The Appendix 4 results, which document the correlation between the liquidity benchmarks in the different ETFs, are high, with the majority being above 0.5 and some being as large as 0.99. This further confirms that the liquidity of ETFs is connected rather than varying by asset class.

[Insert Table 5 About Here]

The quoted spread correlations in Table 6 have a similar pattern to their effective spread counterparts. All 20 Roll, FHT, Effective Tick, Daily Spread, and Amivest correlations are statistically significant, while 19 of the Amihud correlations are statistically significant. As with the effective spread results, the Gibbs, Zeros, and Zeros2 proxies perform well on size and quintile portfolios but are inconsistent on the other subsets of ETFs.

The average correlations are slightly lower than their effective spread counterparts. For instance, the average Daily Spread correlation is 0.797, compared to 0.841 for the Effective Spread results, while the high-low average is 0.712 versus 0.746 in Table 5. However, the ranking of proxies is very similar. Amihud has the third highest average correlation (0.600), Effective Tick is fourth (0.473), and Roll (0.468), FHT (0.415), and Amivest (-0.381) have the next largest correlations.

[Insert Table 6 About Here]

The number of statistically significant correlations with the correct sign is lower for the price impact proxies as compared to both effective and quoted spread. As shown in Table 7, Daily Spread Impact is the best performer with 19 and Amihud and Effective Tick Impact are the second best with 18. Roll Impact, Zeros Impact, and FHT Impact have 16, while Amivest has 13.

Average correlations are also lower for the Price Impact transaction cost benchmark. The Daily Spread Impact measure proxy yields the best result with 0.307, followed by Amihud (0.298), FHT Impact (0.290), and Effective Tick Impact (0.270). The other proxies do not generate consistent results across the bond, commodity, currency, real estate, and other ETFs.

[Insert Table 7 About Here]

3.3.4. RMSEs

While strength of correlations between liquidity proxies and transaction cost benchmarks are the most important consideration for researchers in areas like asset pricing, the ability of proxies to indicate the actual level of transaction costs is important for researchers in areas such as market efficiency. In Table 8 we present Root Mean Squared Errors (RMSEs) for spread proxies against both effective and quoted spread benchmarks. The null hypothesis that the RMSE equals zero cannot be rejected in for any of the ETF groups, which indicates that none of the proxies represent the actual level of transaction costs.

[Insert Table 8 About Here]

3.4. Liquidity Patterns

McInish and Wood (1992) and Chan, Chung, and Johnson (1995) find NYSE stock spreads display a reverse J shape (also referred to a U shape), with spreads highest at the start of the day then declining throughout the day before increasing at the close of trading. In contrast, Chan, Christie, and Schultz (1995), Chan, Chung, and Johnson (1995), and Werner and Kleidon (1996) find Nasdaq, CBOE option, and cross-listed U.K. stock spreads respectively are relatively constant throughout the day and then decline as the market close approaches.

There is also evidence of daily seasonality in liquidity. Foster and Viswanathan's (1990) theoretical model suggests the adverse selection component of the bid-ask spread will be largest on a Monday due to the arrival of information over the weekend when trading cannot take place. Chordia, Sarkar, and Subrahmanyam (2005) and Hameed, Kang, and Viswanathan (2010) find both stock liquidity is higher at the beginning of the week and lower on a Friday. Chordia, Sarkar, and Subrahmanyam (2005) show this relation also holds in bonds. It is more difficult to understand why liquidity may vary across months. However, Chordia, Sarkar, and Subrahmanyam (2005) show U.S. stock and bond liquidity is higher in July through September than the rest of the year.

We now investigate whether there is any variation in ETF transaction costs across different times of the day, week, or year. The existence of such seasonality should be of interest to market participants who have an incentive to minimize transaction costs, and to researchers.

We follow Brockman and Chung (1998) and estimate the following regression:

$$Spread_t = \alpha_1 LnVol_t + \alpha_2 LnPrice_t + \alpha_3 LnVRM_t + \sum_{i=1}^{13} \beta_i Interval_{i,t} + \alpha_4 time + \epsilon_t \tag{14a}$$

$$Spread_t = \alpha_1 LnVol_t + \alpha_2 LnPrice_t + \alpha_3 LnVRM_t + \sum_{i=1}^{5} \beta_i Interval_{i,t} + \alpha_4 time + \epsilon_t \tag{14b}$$

$$Spread_t = \alpha_1 LnVol_t + \alpha_2 LnPrice_t + \alpha_3 LnVRM_t + \sum_{i=1}^{4} \beta_i Interval_{i,t} + \alpha_4 time + \epsilon_t \tag{14c}$$

Where $Spread_t$ is the average effective spread, $LnVol_t$ is the log of volume, $LnPrice_t$ is the log of the last price in an interval, and $LnVRM_t$ is the log of the return variance based on 5-minute midpoint returns over 30 minute intervals, and *time* is a time trend variable. Equation 14a, 14b, and 14c relate to the test for intraday, daily and quarterly seasonality respectively.

The results presented in Table 9 indicate there is strong, statistically significant, evidence of an intraday effect, with spreads larger in the first 30 minutes than at any other point in the day. A decline in spreads between the first and second thirty minute intervals is evident in each ETF subset. However, there is considerable variation in the magnitude of this decline. For instance, currency and commodity ETF spreads decline from 5.91% to 5.80% and 5.53% to 5.37% respectively, whereas the proportional decline for equity ETFs is much larger. For instance, US equity ETF spreads decline from 1.46% to 1.29% and equity sector spreads decline from 1.47% to 1.27%. This variation is consistent with adverse selection models, given the currencies that comprise the currency ETFs are typically trading prior to the start of opening of the US equities markets on which each of the ETFs we consider trades, whereas the equities that underpin the equity ETFs commence trading themselves and have larger spreads on account of the arrival of new information between the prior day's close and the market open.

There is some evidence consistent with the Chan, Christie, and Schultz (1995), Chan, Chung, and Johnson (1995), and Werner and Kleidon (1996) finding that spreads are lower at the end of the day in equity ETFs. However, this is far less pronounced than the larger opening spread effect. The US Equities and Equities Sector ETFs have statistically significantly smaller spreads in the last thirty minute interval than the preceding two intervals and a number of other 30 minute intervals throughout the day. There is no evidence of this in other ETFs and the spreads of Commodity ETFs are actually larger in the last 30 minutes than a number of other intervals.

In contrast to the Chordia, Sarkar, and Subrahmanyam (2005) and Hameed, Kang, and Viswanathan (2010) evidence for stocks, we do not find consistent evidence that ETF spreads on Mondays are smaller than those at the end of the week. US Equity and Equity Sector ETFs have statistically significantly larger spreads on Mondays than Wednesdays and Thursdays, while International Equity, Equity Style, and Other ETFs have larger spreads on Mondays than Tuesdays, Wednesdays, and Thursdays respectively. However, the pattern of larger Monday spreads is not consistent across other days or other ETFs. There is no evidence of spreads being lower on Fridays. The only statistically significant differences involving Friday spreads show larger spreads on Fridays compared to Wednesdays.

The quarterly results reveal a pattern of larger spreads in the fourth quarter. Fourth quarter spreads are statistically significantly larger than those in the other three quarters for US Equities, Equity Style, Currency, and Other ETFs. Moreover, fourth quarter spreads are larger than first quarter spreads for International Equity and Equity Sector ETFs.

[Insert Table 9 About Here]

3.5. Liquidity Shocks and ETF Returns

Amihud and Mendelson (1986) point out that investors will be unlikely to hold less liquid stocks unless they receive a premium for doing so, and subsequent papers, such as

Eleswarapu (1997) and Amihud (2002), find a positive relation between stock illiquidity and returns. Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model where a security's return is influenced by liquidity risk and provide empirical evidence from U.S. equities to support this model. Lee (2011) find liquidity risks are priced in international equity markets, while Lin, Wang, and Wu (2011) find liquidity risk influences the cross-section of bond returns. Sadka (2010) shows liquidity risk is an important determinant of the cross-section of hedge fund returns, while Mancini, Ranaldo, and Wrampelmeyer (2013) show a liquidity risk factor provides a partial explanation for carry trade returns which implies liquidity risk is priced in currencies.

Acharya and Pedersen (2005, p. 376) note their model suggests "a persistent negative shock to a security's liquidity results in low contemporaneous returns and high predicted future returns." However, as Bali, Peng, Shen, and Tang (2014) find, illiquidity and investor inattention lead to underreaction and liquidity shocks are associated with low contemporaneous returns and low future returns.

We investigate the link between liquidity shocks and returns in ETFs. Borkovec, Domowitz, Serbin, and Yegerman (2010) show the 2010 "Flash Crash" affected ETFs much more severely than stocks. They suggest the failure of price discovery in many ETFs was likely caused by a huge decline in liquidity. Moreover, Newman (2015) points out, that on August 24, 2015, an equal weight S&P 500 ETF dropped by over 34%, while the S&P 500 index declined by just 6%.

We follow Bali, Peng, Shen, and Tang (2014) and measure the impact of a liquidity shock as follows. The liquidity shock (LIQU) is the negative difference between our measures of illiquidity, denoted ILLIQ, and their 12-month average:

$$LIQU_{i,t} = -(ILLIQ_{i,t} - AVGILLIQ_{i-t-12,t-1}) \qquad (15)$$

Where $AVGILLIQ_{i-t-12,t-1}$ is the mean of illiquidity over the past 12 months.

Each month, we rank ETFs within each category based on their $LIQU_{i,t}$, as defined in equation 15. We form three portfolios with portfolio 1 containing the ETFs with the largest decline in liquidity (lowest liquidity relative to the average) and portfolio 3 containing ETFs with the smallest liquidity decline (largest liquidity relative to the average). The Table 10 results indicate there is a strong contemporaneous relation between ETF liquidity shocks and returns. The portfolio high - low return is positive and statistically significant for eight of the ten ETF groups when both effective spread and quoted spread are used as illiquidity proxies. This suggests there is clear evidence that when liquidity declines, returns are lower and when liquidity improves returns are higher. This result is most pronounced in "other" ETFs and Equity Sector ETFs, while the relation is not statistically significant in Commodity or Real Estate ETFs.

The Table 11 results confirm the liquidity shock is impounded into returns more quickly than it is for equities. Bali, Peng, Shen, and Tang (2014) document a strong relation between liquidity shocks and the returns the next month. However, our results are much less definitive. The high – low return is not statistically significantly different to zero in any of the ETF groupings based on effective spread, while this return is statistically significantly different to zero in seven of the ten portfolios based on quoted spread. Bali, Peng, Shen, and Tang (2014) suggest the fact that a liquidity shock is not completely reflected in contemporaneous returns of equities could be due to either liquidity frictions and / or investor inattention. Given these explanations, our results imply these factors are less prevalent in ETFs. Lower liquidity frictions in ETFs are certainly consistent with our earlier results which indicate ETF spreads are typically much lower than those for US equities.

[Insert Table 10 About Here]

[Insert Table 11 About Here]

4. Conclusions

We provide a wide-ranging analysis of ETF liquidity using tick and daily data for over 800 ETFs. Our sample includes US, international, market, style, and sector equity ETFs, and bond, commodity, currency, real estate, and "other" ETFs, which include those providing more exotic exposure, such as long – short positions. ETFs have become a very popular with investors, are attracting increased attention from researchers, and have several unique characteristics of ETFs.

First, we find average effective spreads are considerably lower than those documented for stocks. ETF spreads over the 1996-2014 period range from 0.187% for commodities to 0.572% for international equities. Second, we show ETF liquidity spreads are lower than the weighted spread of the stocks that comprise the ETF, which is consistent with the notion that ETFs have lower adverse selection costs.

Third, we find evidence that ETF liquidity movements are correlated with the liquidity of the underlying stocks, which means researchers who wish to avoid the computationally intensive task of measuring the cost of trading all stocks in an index may instead consider using ETF transaction costs as a proxy. We also show that ETF liquidity is influenced by movements in past stock liquidity, while the influence of ETF liquidity on underlying stock liquidity is much weaker. Both supply- and demand-side factors explain ETF liquidity.

Fourth, we show the Roll, Effective Tick, Fong, Holden, and Trzcinka (FHT), Daily Spread, High-Low, Amihud, and Amivest measures all do a good job of proxing for effective spread and quoted spread transaction costs. However, the Daily Spread and High-Low measures are the best performers. Amihud and a Daily Spread Impact measure best mirror movements in the price impact transaction cost.

Fifth, we show effective spreads are larger in the first half hour of trading than at other points of the day in each group of ETFs. Some ETFs have lower spreads at the end of the day, but this is not consistent across all groups. Spreads are larger on Mondays in most ETFs, but this effect is not as strong as that documented in equity markets. Moreover, there is no evidence of lower spreads on Fridays. However, there is evidence of a quarterly effect with spreads spreads are larger in the fourth quarter than other quarters in the majority of ETFs.

Sixth, we show liquidity declines result in lower contemporaneous ETFs returns in eight of the ten ETF groupings. Further, there is evidence that the shock is reflected in returns much more quickly than it is in equities. A possible explanation for this is the lower transaction costs and reduced liquidity frictions in ETFs compared to stocks.

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Table 1: Mean Transaction Costs Over Time

	Overall	1996-1999	2000-2004	2005-2009	2010-2014
Panel A: Effective Spread					
Equities - US	0.271	0.222	0.338	0.336	0.177
Equities - Int	0.572	1.015	0.736	0.420	0.219
Equities - Market	0.505	0.944	0.668	0.348	0.147
Equities - Style	0.258	0.267	0.283	0.304	0.180
Equities - Sector	0.395	0.596	0.405	0.408	0.219
Bonds	0.200	-	0.121	0.300	0.141
Commodities	0.187	-	0.179	0.275	0.106
Currency	0.196	-	-	0.227	0.170
Real Estate	0.290	-	0.280	0.413	0.175
Other	0.404	-	-	0.433	0.382
Panel B: Quoted Spread					
Equities - US	0.345	0.258	0.452	0.430	0.222
Equities - Int	0.751	1.286	0.938	0.563	0.339
Equities - Market	0.662	1.196	0.854	0.476	0.229
Equities - Style	0.326	0.297	0.369	0.387	0.243
Equities - Sector	0.519	0.775	0.545	0.529	0.286
Bonds	0.299	-	0.179	0.441	0.217
Commodities	0.243	-	0.261	0.333	0.140
Currency	0.321	-	-	0.386	0.269
Real Estate	0.342	-	0.339	0.484	0.204
Other	0.497	-	-	0.484	0.507
Panel C: Price Impact					
Equities - US	0.142	0.024	0.100	0.320	0.100
Equities - Int	0.189	0.212	0.173	0.295	0.080
Equities - Market	0.163	0.196	0.152	0.236	0.075
Equities - Style	0.119	0.027	0.082	0.237	0.111
Equities - Sector	0.190	0.128	0.124	0.408	0.086
Bonds	0.197	-	0.054	0.431	0.036
Commodities	0.133	-	0.128	0.185	0.084
Currency	0.138	-	-	0.251	0.045
Real Estate	0.134	-	0.065	0.246	0.085
Other	0.271	-	-	0.416	0.167

Table 1 contains mean effective spreads, quoted spreads, and price impact measures by time period. Cross-sectional averages are calculated each month within each ETF category and time-series averages are then calculated. Each measure is presented in percent.

Table 2: ETF Versus Underlying Liquidity

Panel A: Liquidity Levels

	All	1998-2005	2006-2014
ETF	0.046	0.075	0.021
Underlying	0.050	0.081	0.023
Difference	-0.004	-0.006	-0.002
Difference t-stat	-9.710	-10.600	-3.630

Panel B Correlations

	All	1998-2005	2006-2014
Correlation	0.803	0.826	0.464
p-value	0.000	0.000	0.000

Panel C: Granger Causality

Dependent	Independent	No. lags	Pear	F-stat	p-value
ETF	Underlying	1	0.78	631.3	0
ETF	Underlying	2	0.781	160.04	0
ETF	Underlying	3	0.773	62.76	0
ETF	Underlying	4	0.771	34.29	0
ETF	Underlying	5	0.771	21.05	0
ETF	Underlying	6	0.771	15.67	0
ETF	Underlying	7	0.767	12.25	0
ETF	Underlying	8	0.766	9.56	0
ETF	Underlying	9	0.764	7.92	0
ETF	Underlying	10	0.762	6.98	0
Underlying	ETF	1	0.778	78.32	0
Underlying	ETF	2	0.777	18.73	0
Underlying	ETF	3	0.773	6.41	0
Underlying	ETF	4	0.771	3.05	0.016
Underlying	ETF	5	0.771	2.63	0.022
Underlying	ETF	6	0.767	2.07	0.053
Underlying	ETF	7	0.771	2.05	0.045
Underlying	ETF	8	0.773	2.55	0.009
Underlying	ETF	9	0.767	2.16	0.022
Underlying	ETF	10	0.764	1.99	0.03

Table 2 Panel A contains the levels of effective spreads of the Dow Jones Industrial Average ETF and the weighted average effective spread of the Dow component stocks. Panel B contains the correlations and Panel C has the Granger Causality results.

Table 3: Demand and Supply-Side Liquidity Explanations

		Intercept	ΔVIX	ΔTED	Lag DJIA	Lag Spread	Adj. R^2
				Panel A: ΔVIX			
ETF	coeff	0.000	**0.001**		**-0.001**	**-0.447**	0.214
	t-stat	0.549	7.128		-4.825	-15.032	
Underlying	coeff	0.000	**0.001**		**-0.001**	**-0.413**	0.193
	t-stat	-0.786	6.633		-6.347	-14.156	
Difference	coeff	**-0.002**	**0.001**		0.000	**0.685**	0.470
	t-stat	-5.609	2.820		0.569	33.094	
				Panel B: ΔTED			
ETF	coeff	0.000		**0.031**	**-0.001**	**-0.439**	0.193
	t-stat	0.902		3.227	-3.932	-13.975	
Underlying	coeff	0.000		**0.013**	**-0.001**	**-0.411**	0.177
	t-stat	-0.596		3.160	-5.564	-13.338	
Difference	coeff	**-0.001**		0.012	0.000	**0.686**	0.468
	t-stat	-5.204		1.288	0.510	31.984	
				Panel C: ΔVIX and ΔTED			
ETF	coeff	0.000	**0.001**	**0.026**	**-0.001**	**-0.441**	0.210
	t-stat	1.025	6.901	2.839	-4.656	-14.248	
Underlying	coeff	0.000	**0.001**	**0.010**	**-0.001**	**-0.412**	0.195
	t-stat	-0.492	6.568	2.591	-6.164	-13.501	
Difference	coeff	**-0.001**	**0.000**	0.010	0.000	**0.686**	0.469
	t-stat	-5.173	2.636	1.112	0.278	32.104	

Table 3 contains regression results for the daily effective spread of the Dow Jones Industrial Average ETF and the weighted average effective spread of the Dow component stocks. Independent variables include changes in VIX and the TED Spread.

Table 4: Benchmark and Proxy Means

Panel A: Spread Benchmark and Proxy Means

	N	Effective	Quoted	Roll	Gibbs	Zeros	Zeros2	FHT	Eff Tick	D Spread	High-Low
Equities - US	42,931	0.271	0.345	0.629	0.814	1.137	1.121	0.036	0.030	0.413	0.364
Equities - Int	18,096	0.572	0.751	0.936	0.671	4.632	4.382	0.178	0.061	1.159	0.416
Equities - Market	12,667	0.505	0.662	0.908	0.634	4.283	4.041	0.163	0.056	1.039	0.421
Equities - Style	22,900	0.258	0.326	0.590	0.699	1.054	1.039	0.029	0.024	0.373	0.313
Equities - Sector	25,460	0.395	0.519	0.789	0.965	3.474	3.458	0.137	0.052	0.766	0.418
Bonds	7,905	0.200	0.299	0.306	0.867	3.876	3.772	0.032	0.019	0.222	0.167
Commodities	1,649	0.187	0.243	0.760	0.830	0.874	0.867	0.029	0.026	0.226	0.469
Currency	1,822	0.196	0.321	0.416	1.090	2.094	2.079	0.024	0.023	0.317	0.152
Real Estate	2,244	0.290	0.342	0.683	0.449	0.860	0.769	0.022	0.023	0.391	0.343
Other	13,676	0.404	0.497	1.347	1.706	0.769	0.696	0.031	0.030	0.479	0.649
ETF Size 1	17,542	0.759	0.923	0.891	1.296	4.596	4.010	0.183	0.062	1.471	0.421
ETF Size 2	17,717	0.523	0.666	0.798	0.777	3.664	3.505	0.130	0.051	0.969	0.384
ETF Size 3	17,718	0.438	0.581	0.800	0.552	4.077	3.873	0.148	0.053	0.855	0.422
ETF Size 4	17,717	0.345	0.474	0.750	0.775	3.837	3.639	0.127	0.043	0.706	0.440
ETF Size 5	17,629	0.175	0.250	0.696	0.614	2.352	2.320	0.066	0.027	0.363	0.407
ETF Liquidity 1	17,537	0.768	0.949	0.868	1.613	4.684	3.990	0.163	0.061	1.366	0.390
ETF Liquidity 2	17,718	0.533	0.671	0.754	0.780	4.231	3.959	0.153	0.053	1.038	0.371
ETF Liquidity 3	17,719	0.431	0.566	0.752	0.578	3.901	3.795	0.144	0.051	0.898	0.407
ETF Liquidity 4	17,718	0.334	0.458	0.746	0.563	3.507	3.405	0.120	0.043	0.678	0.428
ETF Liquidity 5	17,631	0.175	0.251	0.820	0.509	2.193	2.165	0.075	0.028	0.361	0.477

Panel B: Price Impact Benchmark and Proxy Means												
	N	Impact	Amihud	Amivest	Pastor	Roll PI	Gibbs PI	Zeros PI	Zeros2 PI	FHT PI	Eff Tick PI	D Spread PI
Equities - US	42,694	0.142	0.100	46,640	(0.004)	5.351	10.670	0.298	4.043	0.298	0.352	6.498
Equities - Int	18,046	0.189	0.219	7,998	(0.005)	9.340	19.686	1.338	33.850	1.338	0.500	16.736
Equities - Market	12,641	0.163	0.184	114,693	(0.003)	5.965	15.119	1.238	32.082	1.238	0.405	13.064
Equities - Style	22,810	0.119	0.081	15,216	(0.003)	3.670	6.898	0.169	2.848	0.169	0.160	3.640
Equities - Sector	25,289	0.190	0.132	7,458	(0.005)	8.593	18.526	0.484	6.953	0.484	0.541	11.685
Bonds	7,888	0.197	0.025	42,755	(0.001)	3.632	2.838	0.559	6.512	0.559	0.095	6.727
Commodities	1,648	0.133	0.032	52,030	-	4.106	2.183	0.047	0.577	0.047	0.043	2.874
Currency	1,821	0.138	0.072	10,221	(0.005)	5.174	7.287	0.239	4.000	0.239	0.120	7.477
Real Estate	2,236	0.134	0.122	11,050	(0.003)	7.041	12.942	0.156	2.606	0.156	0.183	11.734
Other	13,654	0.271	0.192	9,511	(0.004)	14.032	26.252	0.620	5.079	0.620	0.433	17.192
ETF Size 1	17,322	0.383	0.569	151	(0.016)	30.344	53.437	3.042	68.115	3.042	1.667	46.397
ETF Size 2	17,670	0.165	0.173	569	(0.003)	4.060	4.316	1.027	27.278	1.027	0.328	6.729
ETF Size 3	17,693	0.136	0.097	1,981	(0.001)	2.615	6.315	1.044	27.890	1.044	0.248	4.292
ETF Size 4	17,677	0.133	0.050	6,743	-	1.103	2.228	0.530	16.791	0.530	0.115	2.097
ETF Size 5	17,625	0.078	0.010	129,414	-	0.199	0.200	0.133	4.471	0.133	0.025	0.348
ETF Liquidity 1	17,283	0.359	0.634	74	(0.017)	34.217	64.198	4.251	96.911	4.251	1.975	52.480
ETF Liquidity 2	17,701	0.185	0.159	348	(0.002)	2.955	1.993	1.079	28.641	1.079	0.267	5.191
ETF Liquidity 3	17,694	0.145	0.070	1,069	(0.001)	1.187	0.733	0.486	14.607	0.486	0.124	2.090
ETF Liquidity 4	17,680	0.120	0.040	3,894	-	0.558	0.354	0.275	8.296	0.275	0.060	0.868
ETF Liquidity 5	17,629	0.083	0.005	133,536	-	0.095	0.062	0.047	1.285	0.047	0.009	0.128

Table 4 contains means for the Spread benchmarks and proxies (Panel A) and Price Impact benchmarks and proxies (Panel B). Cross-sectional averages are calculated each month within each ETF category and time-series averages are then calculated. Each spread benchmark and proxy is reported as a percentage. Each of the price-impact proxies is multiplied by 10^6, with the exception of the Amivest measure, which is divided by 10^6. The price impact benchmark, which is reported as a percentage, is not scaled.

Table 5: Correlations with the Effective Spread Benchmark

	Roll	Gibbs	Zeros	Zeros2	FHT	Eff Tick	D Spread	High-Low	Amihud	Amivest
Equities - US	**0.536**	0.078	**-0.173**	**-0.181**	**0.303**	**0.585**	**0.743**	**0.831**	**0.746**	**-0.337**
Equities - Int	**0.419**	**0.183**	**0.689**	**0.713**	**0.797**	**0.888**	**0.795**	**0.785**	**0.724**	**-0.763**
Equities - Market	**0.466**	**0.647**	**0.689**	**0.685**	**0.841**	**0.866**	**0.950**	**0.816**	**0.847**	**-0.807**
Equities - Style	**0.326**	**0.445**	**-0.293**	**-0.302**	**0.183**	0.060	**0.790**	**0.642**	**0.236**	**-0.524**
Equities - Sector	**0.458**	**0.548**	**0.248**	**0.241**	**0.730**	**0.638**	**0.890**	**0.745**	-0.030	**-0.827**
Bonds	**0.667**	0.009	-0.125	**-0.142**	**0.545**	**0.431**	**0.821**	**0.839**	**0.680**	**-0.228**
Commodities	**0.411**	0.053	-0.074	**-0.081**	**0.088**	**0.449**	**0.800**	**0.460**	**0.684**	**-0.263**
Currency	**0.738**	-0.021	-0.088	**-0.100**	**0.314**	**0.369**	**0.840**	**0.907**	**0.930**	-0.042
Real Estate	**0.739**	**0.240**	-0.033	**-0.110**	**0.227**	**0.502**	**0.896**	**0.791**	**0.732**	**-0.332**
Other	**0.496**	-0.107	0.003	**-0.221**	**0.432**	**0.121**	**0.889**	**0.642**	**0.586**	0.131
ETF Size 1	**0.538**	**0.296**	**0.374**	**0.341**	**0.636**	**0.643**	**0.905**	**0.894**	**0.658**	**-0.656**
ETF Size 2	**0.536**	**0.496**	**0.511**	**0.500**	**0.816**	**0.799**	**0.940**	**0.809**	**0.838**	**-0.870**
ETF Size 3	**0.511**	**0.686**	**0.503**	**0.502**	**0.785**	**0.817**	**0.943**	**0.760**	**0.813**	**-0.860**
ETF Size 4	**0.405**	**0.655**	**0.334**	**0.334**	**0.719**	**0.687**	**0.939**	**0.661**	**0.819**	**-0.874**
ETF Size 5	**0.259**	**0.448**	**0.047**	**0.047**	**0.558**	**0.453**	**0.908**	**0.529**	**0.824**	**-0.804**
ETF Liquidity 1	**0.611**	**0.278**	**0.388**	**0.354**	**0.661**	**0.713**	**0.904**	**0.890**	**0.701**	**-0.699**
ETF Liquidity 2	**0.536**	**0.545**	**0.531**	**0.529**	**0.815**	**0.865**	**0.931**	**0.842**	**0.844**	**-0.880**
ETF Liquidity 3	**0.473**	**0.679**	**0.341**	**0.337**	**0.678**	**0.730**	**0.949**	**0.755**	**0.846**	**-0.908**
ETF Liquidity 4	**0.380**	**0.554**	**0.276**	**0.276**	**0.693**	**0.583**	**0.942**	**0.674**	**0.844**	**-0.885**
ETF Liquidity 5	**0.123**	**0.319**	0.090	0.090	**0.474**	**0.146**	**0.906**	**0.314**	**0.840**	**-0.797**

Table 5 contains the Spearman correlation coefficients between the spread proxies and the spread benchmark. Following Goyenko, Holden, and Trzcinka (2009), we also include the Amihud and Amivest liquidity proxies. Correlations that are statistically significant at the 10% level or better are in bold. Correlations that are statistically significant and have the expected sign (negative for the Amivest proxy and positive for all other proxies) are in bold, inside a box around them.

Table 6: Correlations with the Quoted Spread Benchmark

	Roll	Gibbs	Zeros	Zeros2	FHT	Eff Tick	D Spread	High-Low	Amihud	Amivest
Equities - US	**0.494**	0.071	**-0.168**	**-0.176**	**0.289**	**0.558**	**0.681**	**0.787**	**0.703**	**-0.325**
Equities - Int	**0.408**	**0.163**	**0.688**	**0.702**	**0.778**	**0.874**	**0.773**	**0.789**	**0.739**	**-0.753**
Equities - Market	**0.448**	**0.623**	**0.676**	**0.672**	**0.825**	**0.870**	**0.945**	**0.813**	**0.848**	**-0.799**
Equities - Style	**0.308**	**0.439**	**-0.258**	**-0.266**	**0.200**	**0.097**	**0.759**	**0.640**	**0.311**	**-0.425**
Equities - Sector	**0.424**	**0.525**	**0.291**	**0.286**	**0.734**	**0.633**	**0.849**	**0.700**	-0.086	**-0.825**
Bonds	**0.639**	-0.016	-0.086	-0.105	**0.423**	**0.467**	**0.895**	**0.919**	**0.720**	**-0.211**
Commodities	**0.407**	0.071	**-0.141**	**-0.148**	**0.043**	**0.331**	**0.805**	**0.576**	**0.589**	**-0.298**
Currency	**0.640**	-0.035	-0.083	-0.096	**0.241**	**0.388**	**0.827**	**0.790**	**0.831**	**-0.015**
Real Estate	**0.465**	0.172	-0.039	**-0.127**	**0.190**	**0.308**	**0.599**	**0.520**	**0.686**	**-0.330**
Other	**0.443**	-0.152	0.042	**-0.155**	**0.426**	**0.203**	**0.836**	**0.589**	**0.662**	**0.166**
ETF Size 1	**0.510**	**0.295**	**0.339**	**0.318**	**0.609**	**0.652**	**0.905**	**0.888**	**0.652**	**-0.667**
ETF Size 2	**0.510**	**0.443**	**0.508**	**0.497**	**0.821**	**0.808**	**0.938**	**0.811**	**0.817**	**-0.865**
ETF Size 3	**0.493**	**0.657**	**0.501**	**0.500**	**0.775**	**0.820**	**0.925**	**0.755**	**0.777**	**-0.837**
ETF Size 4	**0.381**	**0.638**	**0.338**	**0.337**	**0.706**	**0.685**	**0.933**	**0.661**	**0.800**	**-0.852**
ETF Size 5	**0.247**	**0.443**	**0.032**	**0.032**	**0.533**	**0.447**	**0.889**	**0.529**	**0.814**	**-0.783**
ETF Liquidity 1	**0.592**	**0.265**	**0.361**	**0.333**	**0.641**	**0.716**	**0.897**	**0.895**	**0.716**	**-0.691**
ETF Liquidity 2	**0.496**	**0.528**	**0.547**	**0.545**	**0.810**	**0.855**	**0.929**	**0.833**	**0.812**	**-0.870**
ETF Liquidity 3	**0.453**	**0.644**	**0.353**	**0.350**	**0.676**	**0.746**	**0.936**	**0.750**	**0.818**	**-0.885**
ETF Liquidity 4	**0.369**	**0.543**	**0.280**	**0.279**	**0.682**	**0.593**	**0.930**	**0.672**	**0.828**	**-0.867**
ETF Liquidity 5	**0.129**	**0.330**	**0.060**	**0.060**	**0.445**	**0.143**	**0.890**	**0.326**	**0.827**	**-0.776**

Table 6 contains the Spearman correlation coefficients between the spread proxies and the spread benchmark. Following Goyenko, Holden, and Trzcinka (2009), we also include the Amihud and Amivest liquidity proxies. Correlations that are statistically significant at the 10% level or better are in bold. Correlations that are statistically significant and have the expected sign (negative for the Amivest proxy and positive for all other proxies) are in bold, inside a box around them.

Table 7: Correlations with the Price Impact Benchmark

	Amihud	Amivest	Pastor	Roll PI	Gibbs PI	Zeros PI	Zeros2 PI	FHT PI	Eff Tick PI	D Spread PI
Equities - US	**0.526**	0.062	**-0.487**	**0.477**	**0.244**	**0.333**	**0.501**	**0.447**	**0.500**	**0.458**
Equities - Int	**0.438**	**-0.188**	**-0.395**	**0.539**	**0.117**	0.099	**0.111**	**0.192**	**0.469**	**0.280**
Equities - Market	**0.612**	**-0.514**	**-0.323**	**0.540**	**0.595**	**0.481**	**0.453**	**0.536**	**0.543**	**0.584**
Equities - Style	**0.456**	**0.251**	**-0.406**	**0.412**	**0.450**	**0.414**	**0.405**	**0.463**	**0.426**	**0.385**
Equities - Sector	**0.208**	**-0.181**	**-0.139**	**0.241**	**0.196**	**0.402**	**0.446**	**0.462**	**0.275**	**0.167**
Bonds	0.034	-0.071	-0.012	0.044	0.027	0.026	0.046	0.004	**0.172**	**0.114**
Commodities	**0.236**	**-0.199**	0.073	0.097	0.093	0.044	0.020	0.044	**0.190**	**0.209**
Currency	0.016	-0.070	-0.033	0.012	-0.010	0.074	0.145	0.022	0.021	0.015
Real Estate	**0.146**	-0.077	0.086	0.210	0.285	0.034	0.052	0.181	-0.031	**0.315**
Other	**0.309**	**0.099**	**-0.305**	**0.203**	0.048	**0.537**	0.000	**0.545**	**0.135**	**0.539**
ETF Size 1	**0.305**	**-0.037**	**-0.292**	**0.384**	**0.406**	**0.157**	**0.031**	**0.213**	**0.462**	**0.408**
ETF Size 2	**0.432**	**-0.338**	**-0.237**	**0.357**	**0.392**	**0.233**	**0.219**	**0.316**	**0.373**	**0.353**
ETF Size 3	**0.514**	**-0.562**	**-0.231**	**0.529**	**0.528**	**0.352**	**0.344**	**0.515**	**0.508**	**0.568**
ETF Size 4	**0.572**	**-0.594**	**-0.218**	**0.514**	**0.520**	**0.298**	**0.298**	**0.481**	**0.533**	**0.585**
ETF Size 5	**0.412**	**-0.435**	**0.007**	**0.303**	**0.361**	0.016	**0.017**	**0.274**	**0.226**	**0.491**
ETF Liquidity 1	**0.236**	**0.075**	**-0.251**	**0.375**	**0.383**	0.097	**-0.040**	**0.142**	**0.414**	**0.312**
ETF Liquidity 2	**0.514**	**-0.428**	**-0.312**	**0.487**	**0.473**	**0.339**	**0.335**	**0.435**	**0.456**	**0.468**
ETF Liquidity 3	**0.540**	**-0.552**	**-0.250**	**0.529**	**0.522**	**0.181**	**0.181**	**0.423**	**0.468**	**0.592**
ETF Liquidity 4	**0.614**	**-0.649**	**-0.089**	**0.515**	**0.573**	**0.226**	**0.225**	**0.492**	**0.504**	**0.681**
ETF Liquidity 5	**0.354**	**-0.375**	**-0.013**	**0.254**	**0.327**	-0.022	**-0.023**	**0.229**	**0.224**	**0.456**

Table 7 contains the Spearman correlation coefficients between the price impact proxies and the price impact benchmark. Following Goyenko, Holden, and Trzcinka (2009), we also include the Amihud and Amivest liquidity proxies. Correlations that are statistically significant at the 10% level or better are in bold. Correlations that are statistically significant and have the expected sign (negative for the Amivest proxy and positive for all other proxies) are in bold, inside a box around them

Table 8: RMSE

	Effective Spread						Quoted Spread					
	Roll	Gibbs	FHT	High-Low	Eff Tick	CRSP	Roll	Gibbs	FHT	High-Low	Eff Tick	CRSP
Equities - US	1.205	12.501	0.404	0.398	0.403	0.473	1.118	12.469	0.512	0.425	0.518	0.470
Equities - Int	2.516	10.037	0.332	0.213	0.354	0.968	2.521	10.264	0.674	0.431	0.715	0.987
Equities - Market	1.451	10.404	0.258	0.184	0.301	0.899	1.378	10.391	0.433	0.262	0.498	0.827
Equities - Style	0.945	9.852	0.306	0.215	0.323	0.411	1.013	10.028	0.544	0.346	0.577	0.491
Equities - Sector	2.249	14.175	0.513	0.538	0.491	0.669	2.079	14.131	0.637	0.582	0.615	0.641
Bonds	4.900	11.755	1.073	0.644	0.805	0.634	4.729	11.949	1.382	0.635	1.276	0.524
Commodities	1.678	8.178	0.311	0.309	0.306	0.411	1.682	8.168	0.306	0.222	0.303	0.446
Currency	0.849	29.353	0.315	0.211	0.320	0.933	1.009	29.398	0.991	0.721	0.990	0.619
Real Estate	2.681	2.531	0.513	0.464	0.504	1.087	3.115	2.493	0.775	0.887	0.774	1.991
Other	4.927	21.930	1.066	1.085	1.091	0.778	5.073	23.340	1.628	1.425	1.661	0.919
ETF Size 1	4.999	41.504	2.086	1.546	2.003	2.454	4.941	42.304	2.655	1.767	2.642	2.332
ETF Size 2	1.964	13.898	0.432	0.299	0.426	0.426	2.041	14.279	0.825	0.606	0.854	0.558
ETF Size 3	1.961	3.285	0.147	0.185	0.148	0.232	1.887	3.297	0.260	0.221	0.264	0.246
ETF Size 4	1.591	4.422	0.081	0.214	0.081	0.148	1.599	4.532	0.265	0.310	0.269	0.262
ETF Size 5	1.613	4.236	0.029	0.208	0.026	0.055	1.555	4.228	0.062	0.195	0.060	0.069
ETF Liquidity 1	4.874	45.287	2.176	1.577	2.100	2.297	4.943	46.451	3.011	2.022	3.014	2.277
ETF Liquidity 2	1.719	10.572	0.370	0.199	0.356	0.535	1.689	10.607	0.545	0.333	0.556	0.597
ETF Liquidity 3	1.322	4.644	0.122	0.113	0.124	0.299	1.321	4.726	0.286	0.206	0.292	0.362
ETF Liquidity 4	1.491	3.472	0.080	0.188	0.080	0.127	1.428	3.490	0.168	0.192	0.170	0.160
ETF Liquidity 5	2.730	3.445	0.032	0.379	0.027	0.055	2.651	3.430	0.065	0.353	0.062	0.070

Table 8 contains the Root Mean Squared Errors. Those in bold indicate the null hypothesis that the RMSE equals zero can be rejected at the 10% level.

Table 9: Seasonality

	Equities - US	Equities - Int	Equities - Market	Equities - Style	Equities - Sector	Bonds	Commodities	Currency	Real Estate	Other
					Panel A: Intraday					
Int01	1.464#	3.043#	2.418#	2.240#	1.469#	3.058	5.527	5.913#	3.075	3.544#
Int02	1.290*	2.892*#	2.330*	2.076*	1.270*	2.908*	5.372*	5.795*	2.874*	3.365*
Int03	1.285*	2.863*	2.273*	2.096*	1.249*	2.912*	5.345*#	5.817*	2.956	3.377*
Int04	1.292*	2.860*	2.268*	2.082*	1.272*#	2.993	5.335*#	5.787	2.943*	3.372*
Int05	1.308*	2.862*	2.277*	2.109*	1.274*	2.890*	5.361*	5.764*	2.947*	3.363*
Int06	1.313*#	2.840*	2.279*	2.107*#	1.267*	2.899*	5.314*#	5.770*	2.903*	3.421*
Int07	1.312*#	2.868*	2.249*	2.101*#	1.298*#	2.887*#	5.333*#	5.777*	2.991	3.379*
Int08	1.304*	2.840*	2.242*	2.112*	1.264*	2.910*	5.338*#	5.811*	2.990	3.376*
Int09	1.410	2.851*	2.267*	2.297*	1.277*	2.925*	5.328*#	5.732*#	2.928*	3.366*
Int10	1.302*	2.851*	2.260*	2.114*	1.259*	2.977	5.333*#	5.762*	2.965*	3.368*
Int11	1.312*#	2.856*	2.251*#	2.116*#	1.279*#	2.929*	5.361*#	5.866	2.869*	3.394*
Int12	1.308*#	2.863*	2.270*	2.097*	1.285*#	2.905*#	5.352	5.765*	2.905*	3.375*
Int13	1.282*	2.857*	2.295*	2.079*	1.246*	3.003	5.398	5.774*	2.985	3.385*
lnP	-0.410	-0.677	-0.551	-0.455	-0.488	-0.285	-0.476	-1.372	-0.725	-0.616
lnV	-0.016	-0.025	-0.023	-0.018	-0.017	-0.029	-0.050	0.003	-0.004	-0.042
lnVRm	0.158	0.108	0.093	0.141	0.164	0.075	0.140	0.096	0.217	0.240
Time	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.000
N	9049	10921	15044	8320	8566	8475	16401	8703	10010	7921
Adj R^2	0.577	0.660	0.650	0.547	0.625	0.534	0.663	0.566	0.592	0.583
					Panel B: Daily					
Int01	1.556	2.886	2.272#	2.384	1.455	3.204	5.259	6.025	2.143#	3.030
Int02	1.547	2.876	2.266	2.390*	1.432*	3.216	5.233	6.006	2.143	3.016
Int03	1.524*#	2.879	2.248	2.358#	1.429*#	3.222	5.241	6.003	2.122#	3.027
Int04	1.537*	2.885	2.262	2.380	1.430	3.217	5.253	6.046	2.115#	3.006#
Int05	1.546	2.885	2.258	2.380	1.447	3.194	5.272*	6.056	2.175	3.046

lnP	-0.416	-0.675	-0.545	-0.477	-0.480	-0.348	-0.473	-1.460	-0.549	-0.577
lnV	-0.013	-0.020	-0.016	-0.014	-0.016	-0.022	-0.043	0.004	0.000	-0.038
lnVRm	0.163	0.113	0.097	0.147	0.170	0.076	0.145	0.096	0.214	0.247
Time	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.000
N	9049	10921	15044	8320	8566	8475	16401	8703	10010	7921
Adj R^2	0.571	0.654	0.645	0.541	0.619	0.530	0.656	0.563	0.587	0.577
Panel C: Quarterly										
Int01	1.598#	2.701#	3.423	1.627#	1.581#	2.552	4.926	6.485#	7.145	2.394#
Int02	1.554#	2.759*	3.333	1.592#	1.610#	2.528	4.835#	6.501#	7.227	2.345#
Int03	1.595#	2.752*	3.376	1.599#	1.648	2.606	4.815	6.521#	7.249	2.410#
Int04	1.647*	2.752*	3.428	1.660*	1.661*	2.586	4.858	6.594*	7.073	2.508*
lnP	-0.447	-0.719	-0.491	-0.433	-0.610	-0.407	-0.433	-1.673	-0.716	-0.512
lnV	-0.014	-0.021	-0.018	-0.015	-0.016	-0.026	-0.041	0.006	0.003	-0.035
lnVRm	0.160	0.111	0.092	0.144	0.167	0.072	0.140	0.093	0.219	0.238
Time	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	-0.001	0.000
N	9049	10921	15044	8320	8566	8475	16401	8703	10010	7921
Adj R^2	0.577	0.657	0.648	0.545	0.626	0.534	0.660	0.569	0.592	0.586

Table 9 documents intraday (Panel A), daily (Panel B), and Quarterly (Panel C) seasonality in effective spreads. $LnVol_t$ is the average log of volume, $LnPrice_t$ is the average log of price, and $LnVRM_t$ is the average log of the return on market over 30 minute intervals, and *time* is a time trend variable. * (#) indicates the coefficient is different to the last (first) coefficient within the day (Panel A), week (Panel B), and quarter (Panel C).

Table 10: Liquidity Shock and Contemporaneous Returns

		Effective Spread				Quoted Spread			
		1 (Low)	2	3 (High)	High - Low	1 (Low)	2	3 (High)	High - Low
Equities - US	Coefficient	0.002	0.008	0.011	0.007	0.001	0.008	0.012	0.010
	p-value	0.630	0.020	0.000	0.050	0.810	0.010	0.000	0.000
Equities - Int	Coefficient	0.002	0.006	0.012	0.008	0.001	0.006	0.013	0.012
	p-value	0.640	0.080	0.000	0.000	0.900	0.080	0.000	0.000
Equities - Market	Coefficient	0.002	0.007	0.012	0.009	0.001	0.007	0.013	0.012
	p-value	0.580	0.050	0.000	0.000	0.740	0.080	0.000	0.000
Equities - Style	Coefficient	0.005	0.009	0.007	0.004	0.005	0.009	0.008	0.004
	p-value	0.210	0.000	0.040	0.070	0.240	0.000	0.030	0.030
Equities - Sector	Coefficient	-0.002	0.003	0.011	0.012	-0.004	0.004	0.012	0.017
	p-value	0.630	0.460	0.010	0.000	0.350	0.310	0.000	0.000
Bonds	Coefficient	0.001	0.005	0.005	0.004	0.001	0.005	0.005	0.004
	p-value	0.390	0.000	0.000	0.010	0.370	0.000	0.000	0.010
Commodities	Coefficient	0.001	0.006	0.008	0.003	0.000	0.007	0.008	0.004
	p-value	0.850	0.250	0.170	0.280	0.950	0.230	0.180	0.140
Currency	Coefficient	-0.001	0.002	0.004	0.010	0.000	0.002	0.003	0.007
	p-value	0.790	0.430	0.060	0.000	0.900	0.410	0.160	0.010
Real Estate	Coefficient	0.01	0.011	0.009	-0.001	0.011	0.010	0.009	-0.001
	p-value	0.030	0.020	0.070	0.670	0.020	0.020	0.070	0.520
Other	Coefficient	-0.013	-0.005	0.002	0.014	-0.016	-0.005	0.005	0.020
	p-value	0.002	0.008	0.011	0.007	0.000	0.060	0.160	0.000

Table 10 documents the relation between a monthly liquidity shock and returns that month. The liquidity shock (LIQU) is the negative difference between either effective spread or quoted spread, and their 12-month average. Each month we rank ETFs within each category based on their LIQU. We form three portfolios with portfolio 1 containing the ETFs with the biggest decline in liquidity (lowest liquidity relative to the average) and portfolio 3 containing ETFs with the smallest liquidity decline (largest liquidity relative to the average). The returns to these portfolios in the month of the shock are then recorded.

Table 11: Liquidity Shock and Lead Returns

		Effective Spread				Quoted Spread			
		1 (Low)	2	3 (High)	High - Low	1 (Low)	2	3 (High)	High - Low
Equities - US	Coefficient	0.006	0.008	0.007	-0.001	0.001	0.008	0.012	0.010
	p-value	0.140	0.020	0.030	0.700	0.810	0.010	0.000	0.000
Equities - Int	Coefficient	0.006	0.007	0.007	0.001	0.001	0.006	0.013	0.012
	p-value	0.150	0.070	0.060	0.500	0.900	0.080	0.000	0.000
Equities - Market	Coefficient	0.007	0.007	0.008	0.001	0.001	0.007	0.013	0.012
	p-value	0.110	0.060	0.050	0.810	0.740	0.080	0.000	0.000
Equities - Style	Coefficient	0.007	0.008	0.006	-0.002	0.005	0.009	0.008	0.004
	p-value	0.070	0.010	0.120	0.490	0.240	0.000	0.030	0.030
Equities - Sector	Coefficient	0.003	0.003	0.005	0.002	-0.004	0.004	0.012	0.017
	p-value	0.470	0.500	0.150	0.430	0.350	0.310	0.000	0.000
Bonds	Coefficient	0.003	0.004	0.005	0.002	0.001	0.005	0.005	0.004
	p-value	0.030	0.000	0.010	0.240	0.370	0.000	0.000	0.010
Commodities	Coefficient	0.007	0.005	0.005	-0.002	0.000	0.007	0.008	0.004
	p-value	0.210	0.370	0.350	0.530	0.950	0.230	0.180	0.140
Currency	Coefficient	0.002	0.000	0.003	0.001	0.000	0.002	0.003	0.007
	p-value	0.390	0.860	0.200	0.640	0.900	0.410	0.160	0.010
Real Estate	Coefficient	0.011	0.009	0.010	-0.001	0.011	0.010	0.009	-0.001
	p-value	0.030	0.040	0.060	0.470	0.020	0.020	0.070	0.520
Other	Coefficient	-0.007	-0.005	-0.003	0.005	-0.016	-0.005	0.005	0.020
	p-value	0.000	0.020	0.240	0.230	0.000	0.060	0.160	0.000

Table 11 documents the relation between a monthly liquidity shock and returns the following month. The liquidity shock (LIQU) is the negative difference between either effective spread or quoted spread, and their 12-month average. Each month we rank ETFs within each category based on their LIQU. We form three portfolios with portfolio 1 containing the ETFs with the biggest decline in liquidity (lowest liquidity relative to the average) and portfolio 3 containing ETFs with the smallest liquidity decline (largest liquidity relative to the average). The returns to these portfolios in the month following the shock are then recorded.

Figure 1: Dow Jones ETF and Underlying Stock Effective Spreads

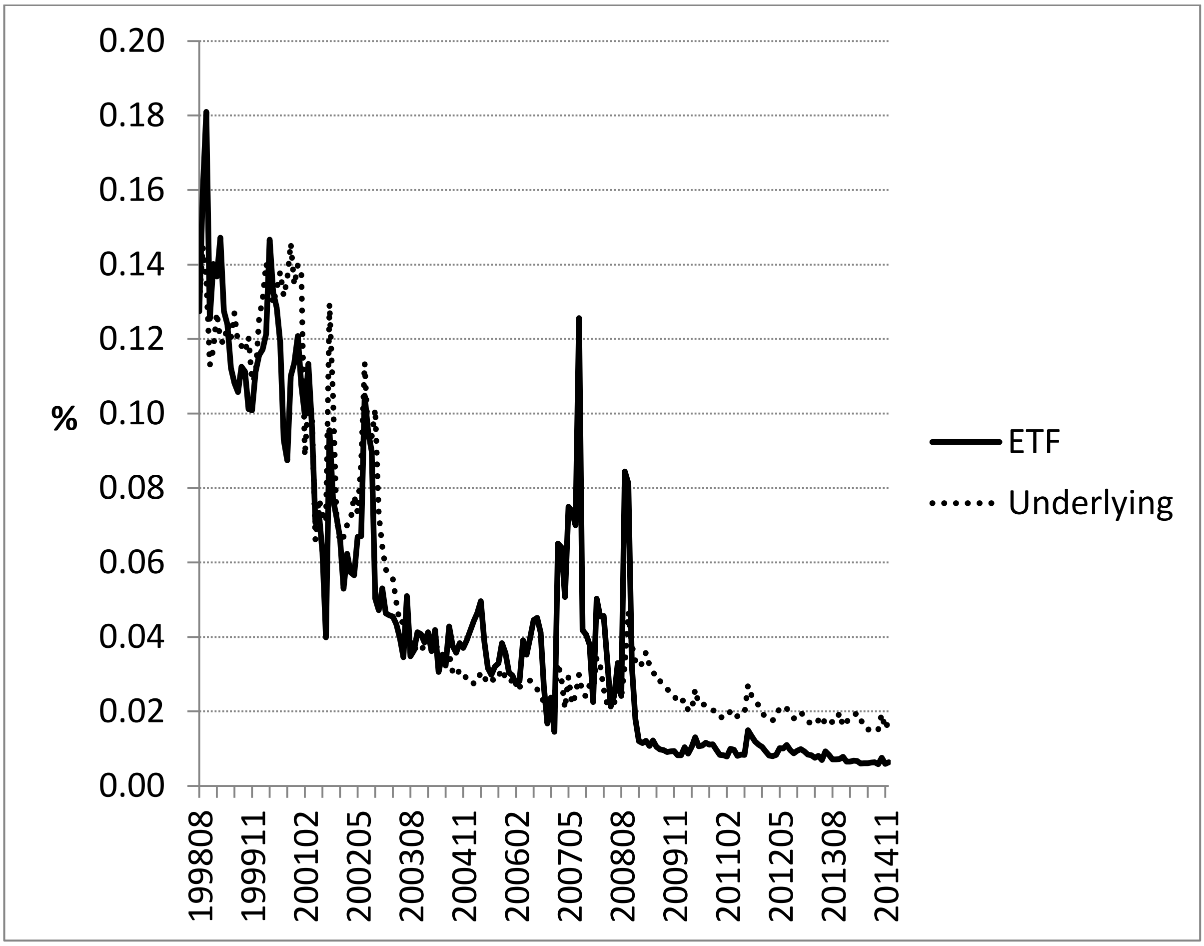
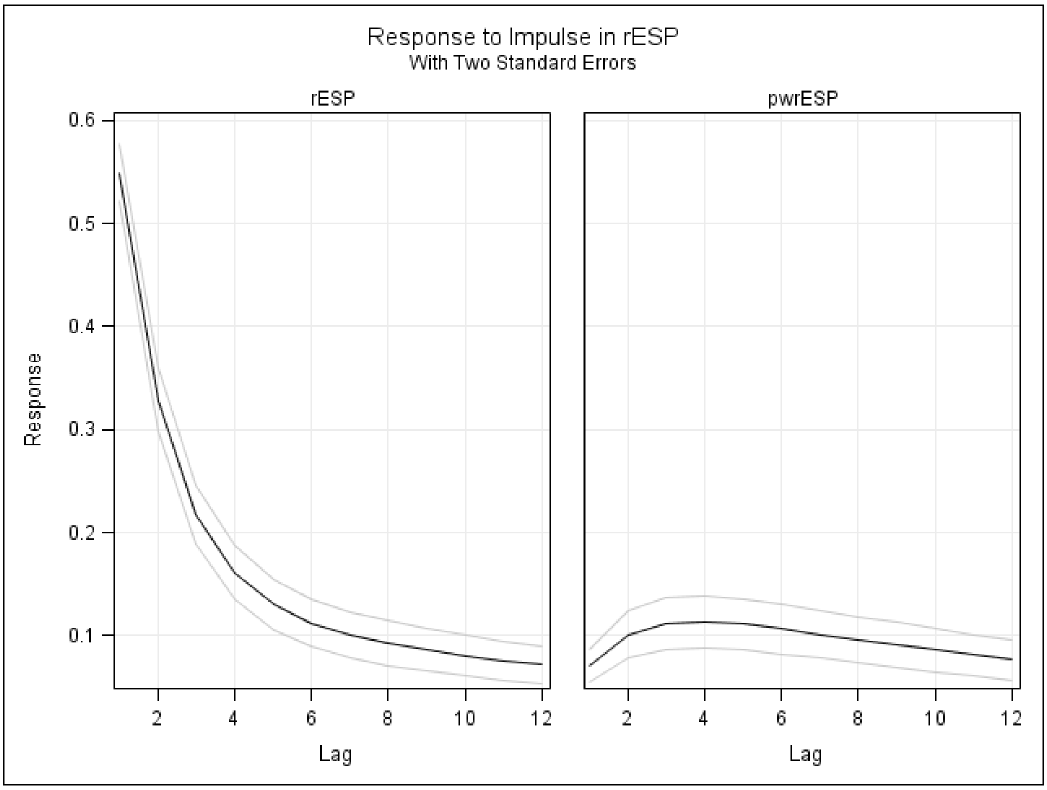
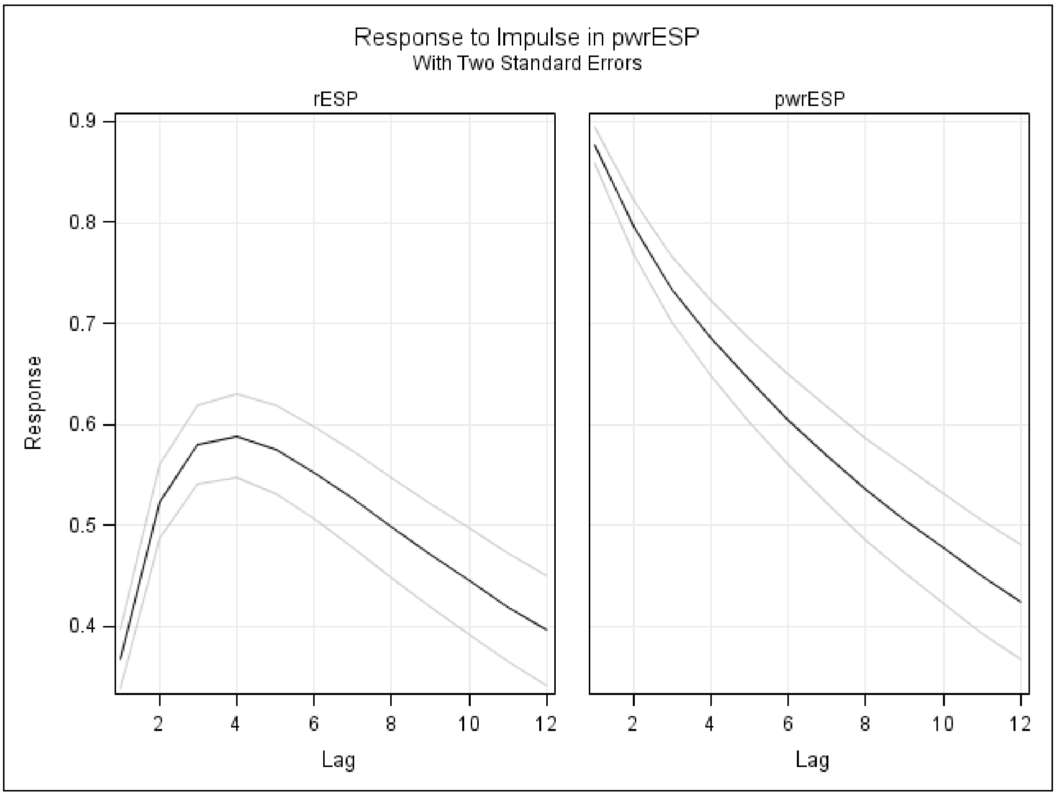


Figure 2: Dow Jones ETF and Underlying Stock Effective Spread Impulse Response Functions





Impulse response functions where rESP is the ETF effective spread and pwrESP is the weighted Dow Jones Industrial Average component stock effective spread.

Appendix 1: Number of ETFs by Year

Year	Equities - US	Equities - Int	Equities - Market	Equities - Style	Equities - Sector	Bonds	Commodities	Currency	Real Estate	Other
1996	2	17	17	1	1	-	-	-	-	-
1997	2	17	17	1	1	-	-	-	-	-
1998	12	17	17	3	9	-	-	-	-	-
1999	14	17	17	3	11	-	-	-	-	-
2000	61	24	27	24	34	-	-	-	1	-
2001	76	30	30	28	48	-	1	-	3	-
2002	80	32	32	29	51	5	1	-	3	-
2003	85	34	34	33	52	7	1	-	3	-
2004	112	36	37	53	58	6	2	-	4	-
2005	156	42	40	76	82	6	3	1	4	-
2006	246	66	42	129	141	8	7	8	5	14
2007	333	111	65	165	214	50	12	11	22	74
2008	378	136	84	187	243	60	15	18	25	124
2009	373	158	97	205	229	78	16	19	18	152
2010	344	150	88	201	205	78	14	19	18	152
2011	322	139	86	187	188	77	14	19	18	139
2012	291	131	84	169	169	75	13	17	18	137
2013	284	127	83	161	167	74	13	14	18	130
2014	271	127	83	153	162	73	13	14	18	127

Appendix 1 contains the number of ETFs by year.

Appendix 2: Median Transaction Costs Over Time

	Overall	1996-1999	2000-2004	2005-2009	2010-2014
Panel A: Effective Spread					
Equities - US	0.174	0.185	0.315	0.173	0.091
Equities - Int	0.373	0.981	0.752	0.291	0.129
Equities - Market	0.322	0.976	0.732	0.196	0.074
Equities - Style	0.182	0.235	0.238	0.172	0.100
Equities - Sector	0.252	0.622	0.374	0.205	0.120
Bonds	0.081	-	0.067	0.128	0.072
Commodities	0.110	-	0.150	0.151	0.048
Currency	0.080	-	-	0.124	0.058
Real Estate	0.191	-	0.263	0.216	0.115
Other	0.150	-	-	0.232	0.132
Panel B: Quoted Spread					
Equities - US	0.219	0.215	0.400	0.219	0.127
Equities - Int	0.521	1.246	0.977	0.395	0.210
Equities - Market	0.455	1.227	0.925	0.302	0.120
Equities - Style	0.228	0.272	0.296	0.212	0.150
Equities - Sector	0.343	0.833	0.466	0.261	0.161
Bonds	0.128	-	0.104	0.201	0.124
Commodities	0.168	-	0.221	0.239	0.073
Currency	0.115	-	-	0.133	0.091
Real Estate	0.247	-	0.329	0.277	0.168
Other	0.200	-	-	0.247	0.182
Panel C: Price Impact					
Equities - US	0.046	0.019	0.067	0.060	0.040
Equities - Int	0.099	0.163	0.135	0.070	0.050
Equities - Market	0.085	0.147	0.121	0.061	0.042
Equities - Style	0.046	0.031	0.062	0.052	0.039
Equities - Sector	0.068	0.137	0.089	0.068	0.047
Bonds	0.028	-	0.032	0.033	0.025
Commodities	0.047	-	0.120	0.040	0.036
Currency	0.023	-	-	0.017	0.024
Real Estate	0.058	-	0.066	0.067	0.051
Other	0.064	-	-	0.069	0.062

Appendix 2 contains median effective spreads, quoted spreads, and price impact measures. Cross-sectional medians are calculated each month within each ETF category and time-series medians are then calculated. Each measure is presented in percent.

Appendix 3: Mean Transaction Costs Over Time by Quintile

	Overall	1996-1999	2000-2004	2005-2009	2010-2014
Panel A: Effective Spread					
ETF Size 1	0.759	1.188	0.653	0.684	0.612
ETF Size 2	0.523	0.977	0.531	0.430	0.245
ETF Size 3	0.438	0.961	0.475	0.311	0.127
ETF Size 4	0.345	0.797	0.363	0.231	0.078
ETF Size 5	0.175	0.371	0.220	0.118	0.037
ETF Liquidity 1	0.768	1.093	0.722	0.701	0.632
ETF Liquidity 2	0.533	1.016	0.550	0.423	0.238
ETF Liquidity 3	0.431	0.963	0.438	0.318	0.127
ETF Liquidity 4	0.334	0.828	0.322	0.215	0.069
ETF Liquidity 5	0.175	0.384	0.213	0.118	0.034
Panel B: Quoted Spread					
ETF Size 1	0.923	1.429	0.815	0.797	0.768
ETF Size 2	0.666	1.209	0.676	0.550	0.338
ETF Size 3	0.581	1.250	0.624	0.413	0.195
ETF Size 4	0.474	1.039	0.492	0.348	0.129
ETF Size 5	0.250	0.478	0.314	0.196	0.065
ETF Liquidity 1	0.949	1.335	0.900	0.854	0.797
ETF Liquidity 2	0.671	1.263	0.703	0.513	0.323
ETF Liquidity 3	0.566	1.227	0.576	0.418	0.198
ETF Liquidity 4	0.458	1.080	0.436	0.319	0.121
ETF Liquidity 5	0.251	0.495	0.310	0.201	0.057
Panel C: Price Impact					
ETF Size 1	0.383	0.261	0.168	0.787	0.287
ETF Size 2	0.165	0.178	0.122	0.289	0.072
ETF Size 3	0.136	0.192	0.122	0.183	0.059
ETF Size 4	0.133	0.173	0.109	0.206	0.052
ETF Size 5	0.078	0.084	0.076	0.122	0.032
ETF Liquidity 1	0.359	0.174	0.166	0.788	0.265
ETF Liquidity 2	0.185	0.222	0.136	0.297	0.094
ETF Liquidity 3	0.145	0.218	0.109	0.207	0.063
ETF Liquidity 4	0.120	0.185	0.098	0.165	0.044
ETF Liquidity 5	0.083	0.073	0.090	0.129	0.036

Appendix 3 contains mean effective spreads, quoted spreads, and price impact measures by time period. Cross-sectional means are calculated each month within each ETF category and time-series means are then calculated. Each measure is presented in percent.

Appendix 4: Correlations By ETF Type

	Equities - Mkt	Equities - Sty	Equities - US	Equities - Int	Equities - Sec	Real Estate	Commodities	Bonds	Currency
Panel A: Effective Spread									
Equities - Style	0.513								
Equities - US	0.436	0.927							
Equities - Int	0.987	0.573	0.479						
Equities - Sector	0.795	0.750	0.631	0.822					
Real Estate	0.483	0.850	0.809	0.557	0.809				
Commodities	0.477	0.695	0.710	0.545	0.735	0.747			
Bonds	0.529	0.770	0.782	0.595	0.807	0.692	0.751		
Currency	0.749	0.723	0.726	0.734	0.723	0.695	0.486	0.676	
Other	0.681	0.641	0.682	0.617	0.662	0.620	0.570	0.521	0.624
Panel B: Quoted Spread									
Equities - Style	0.438								
Equities - US	0.409	0.926							
Equities - Int	0.986	0.500	0.441						
Equities - Sector	0.817	0.635	0.544	0.832					
Real Estate	0.447	0.638	0.652	0.452	0.643				
Commodities	0.587	0.732	0.738	0.610	0.732	0.601			
Bonds	0.516	0.843	0.745	0.613	0.750	0.578	0.773		
Currency	0.840	0.840	0.804	0.843	0.801	0.492	0.671	0.777	
Other	0.610	0.595	0.580	0.593	0.572	0.375	0.583	0.547	0.707

Appendix 4 contains monthly correlations.