An Intertemporal Study of ETF Liquidity and Underlying Factor Transition, 2009–2014

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Agrrawal and Clark [2009] identified a set of primary factors that are indicative of an exchange-traded fund's liquidity. This article is a sequel study that tracks the migration of the now well-established exchange-traded fund (ETF) asset class, with respect to trading liquidity and its constituent factors over a five-year period (2009–2014). Including more than 400 ETFs ranging from $31 billion to $1.7 million in market capitalization, this study covers a market segment with a total of $2.112 trillion in ETF denominated assets. In addition to a factor transition matrix and attributes on each of the four liquidity factors, this study includes the CAPM betas for all the ETFs in the dataset, and a top 50 list of the most liquid ETFs traded on U.S. exchanges.

As of April 2014, we tracked the liquidity of 462 ETFs that went back to 2009 (with a $1 million market capitalization cutoff) and had complete fields for the four factors that are the determinants of our ranking algorithm. The aggregate market cap for this set was calculated to be $438 billion in January 2009 and $2.112 trillion in April 2014. This represents a 34.9% annual growth rate in ETFs, compared with a 19.8% annual growth rate in the Russell 3000 and a 4.5% growth in the Lehman Aggregate Bond Index over the five-year period.[1] This in itself can be indicative of the growth of this asset class above what could be attributed to market driven appreciation.[2] In the subsequent exhibits, we will show how the bid–ask spreads (B-A spreads) and expense ratios have compressed and trading volumes along with market capitalization have increased over time, all of these factors are constituents of the A-C liquidity score (Agrrawal and Clark [2009]).

We have reasons to think that ETF liquidity has indeed grown over time for most assets and that ETFs have rapidly become a viable and efficient instrument in the asset management ecosystem. While that is good news for market efficiency, we also notice that there has been an upward drift in the betas of the ETFs, which can be indicative of higher asset correlations (both within and between asset types), sector intertwining, global market co-integration, and overlapping core constituents in ETFs or could be simply due to a systematic upward drift in overall market risk premium. This may impact portfolio diversification benefits if similar ETFs are included without a thorough examination of the underlying correlation structures (Agrrawal [2013]). A factor migration matrix that shows the direction of change in the factor deciles of each liquidity determinant is discussed in the article and confirms the regression analysis results. Based on the A-C liquidity scores, a top 50 liquidity list is also generated.

Our study represents the first academic analysis of intertemporal transition in the determinants of ETF liquidity and a lack of association with the CAPM beta. The study also utilizes the A-C liquidity scoring algorithm for ranking funds based on readily available factors. The results of this study should be of interest to firms developing new ETF products as well as to investors, both institutional and retail and regulators. Following Chordia et al. [2008], a study of liquidity is also a study of market efficiency. The issue of liquidity for ETFs will continue to gain in importance, as more managers and advisers use ETFs for asset allocation and risk management with the increasingly popular optimizers that control downside risk (Kale [2006], Waggle and Agrrawal [2006], Xiong and Idzorek [2011], Kale and Sheth [2013]). By developing a rank ordering of ETFs from the most liquid to the least liquid based on four easily observable variables, this article contributes to making the evolution of the ETF asset class more transparent and hence improving the efficiency of the ETF market. Additionally, by studying the migration of liquidity over the 2009–2014 period, we assess the stability of the ETF market space and the underlying liquidity proxies.

DETERMINANTS OF LIQUIDITY

As ETFs have become more popular for both individual and institutional investors, it is important to understand the determinants of liquidity. Ryan and Follet [2001] linked ETF liquidity to the liquidity of the underlying index. Kittsley and Edrosolan [2008] found that in the secondary market, bid–ask spread and trading volume are important determinants of liquidity as well. Recent works by Ben-David et al. [2014] and Krause et al. [2013] indicated that volatility spillovers from ETFs to component stocks are significant and result from underlying arbitrage activity. This is a major shift from the classic understanding that the effect runs one way—from the underlying stocks to the ETFs only.

Previous research on ETF liquidity had suggested that there are no liquidity issues due to the creation/redemption activities of the market makers (McNally [2001]; see also, Ryan and Follet [2001]). However, Borkovec and Serbin [2013] found the limit order book for ETFs to be deeper than that of common stocks and urged caution in equating ETF liquidity with that of the underlying stocks. The work of Dodd and Edrosolan [2008] indicated that the unique mechanism of creation/redemption units and the liquidity of the constituent stocks in the ETFs is not sufficient to explain ETF liquidity—“tighter spreads than that of the underlying basket have emerged for several ETFs due to their own robust trading volume.” Yu and Webb [2009] found a post-split deterioration of liquidity as evidenced by wider bid–ask spreads. Giulianini [2012] showed that a fragmented market can negatively affect liquidity as a result of higher fees, penalties, and buy-ins. Hassine and Roncalli T [2013] highlighted the role of liquidity spread in measuring the efficiency of an ETF and mentioned it as a factor forgotten by supervisory authorities.

The current research consensus lies in the creation/redemption activities of market makers as not being the only influence on liquidity. The development and utilization of a multi-factor quantitative liquidity score for the evaluation of ETF trading depth is thus an improvement over what is a primarily abstract belief that the issuers of the ETFs will somehow ensure adequate liquidity through the creation/redemption process. It is definitely of little value to the retail investor or the fast-moving trader who does not have access to the issuing desks of these ETFs.

Our liquidity ranking mechanism utilizes the A-C liquidity score (Agrrawal and Clark [2009]) that is algorithmically derived from the factors that are discussed in the literature as the primary liquidity measures and have an intuitive basis. Amihud and Mendelson [1980] suggested using bid–ask spread as a measure of liquidity. Stoll and Whaley [1983] found that stocks of large firms tend to be more liquid than small firms, so we use size as a liquidity variable to proxy the depth of the market. Chordia et al. [2008] found that liquidity stimulates arbitrage activity and thus lower transaction cost markets (expense ratios) tend to be more efficient. Garbade and Silber [1982] found that assets with higher trading volumes tend to be more liquid. Kyle [1985] referred to this as a measure of “depth.” Yan [2008] recognized that high-turnover funds would tend to have higher transactions costs as well as adverse tax impacts on taxable investors, leading to lower liquidity. The factors we find significant for the ETF liquidity score in this article are the bid–ask spread, asset size, expense ratios, and trading volume. The 2009 version of the A-C liquidity measure has annual turnover as the fifth factor, but it is now excluded due to its low marginal contribution.

Retail investors do not have access to such creation/redemption activities and a thinly traded ETF can have wide bid–ask spreads due to asynchronous trading and limited investor interest in the ETF despite the underlying assets being very liquid, especially during periods of high market volatility and during market open/close times. Large intraday bid–asks are often indicative of such liquidity asymmetry, the resultant spreads can significantly diminish the total return on a roundtrip trade.

Following the techniques of the Agrrawal [2009] data harvester, the bid–ask spreads and other fields are drawn from several internet-based sources, including Morningstar and CSI data that are provided for web applications such as Yahoo! Finance and Google Finance. To approximate a Gaussian distribution and minimize outlier impact, all variables are subjected to the natural log transformation. The sample is limited to ETFs that had complete information for all of the following four variables: total assets under management, average trading volume, average bid–ask spread, and management fees over the 2009–2014 period (a total of 462 ETFs). These ETFs ranged from $31 billion to $1.7 million in market capitalization, aggregating $2.112 trillion in ETF-denominated assets. It may be noted that these same ETFs were valued at only $438 billion in January 2009.

FOUR LIQUIDITY FACTORS

Exhibit 1 provides descriptive statistics for the four significant variables (we drop annual turnover from the original 2009 specification due to insufficient significance on the variable, resulting from the fact that the vast majority of ETFs have low annual turnovers, which is by design an attribute of most ETFs). The large differences between the mean and median for each of these variables as well as the minimum and maximum values are indicative of dispersion between the largest and smallest funds in the ETF market and why it is important for the investor to understand the differential.

Exhibit 2 looks at the correlations among our liquidity factors. Consistent with expectations, we find that there is a negative relationship between the bid–ask spread and both the size and trading volume variables, which tells us that the low bid–ask spread ETFs are typically larger and have higher trading volumes (liquidity attributes). We also find that there is a positive correlation between the bid–ask spread and the expense ratio, which suggests that bid–ask spreads tend to rise as expenses rise, indicating that investors have lower interest levels in the more expensive ETFs, which perhaps drives their volumes and liquidity to even lower levels, eventually leading to extinction. Our ranking criterion easily identifies such illiquid securities. Low-expense ETFs have lower bid–ask spreads, as can be seen in the 0.233 correlation. Size (market capitalization) is positively correlated with volume and negatively correlated with expense ratio, suggesting larger ETFs tend to have higher trading volume as well as lower expenses. The A-C liquidity score is positively linked to the bid–ask spreads and expense ratios and negatively

EXHIBIT 1
Descriptive Statistics of Liquidity Variables, 2014 Values

Factor	Mean	Median	Minimum	Maximum	Std. Dev.
Bid–Ask Spread (bps)	13.67	7.17	0.53	350.52	26.03
Size ($)	3.9 B	578 M	1.7 M	158.1 B	11.8 B
Expense Ratio (%)	0.49	0.50	0.05	1.07	0.24
Avg. Trading Volume (3 mo.)	1.9 M	125,030	458	112.8 M	8.0 M

EXHIBIT 2
Correlation Matrix of Liquidity Determinants, 2014 Values

Correlations/ P-Values	A-C Liquidity Score	Bid–Ask Spread (bps)	Size ($)	Expense Ratio (%)	Avg. Volume (3 mo.)
A-C Liquidity Score	—	p-val 0.000	p-val 0.000	p-val 0.000	p-val 0.000
Bid–Ask Spread (bps)	0.531	—	p-val 0.026	p-val 0.000	p-val 0.038
Size ($)	*–0.317*	–0.104	—	p-val 0.000	p-val 0.000
Expense Ratio (%)	0.452	0.233	–0.286	—	p-val 0.027
Avg. Volume (3 mo.)	*–0.309*	–0.097	0.392	–0.103	—

Notes: A low A-C Liquidity score is indicative of higher ETF liquidity. The off-diagonal cells in the upper triangular matrix have the p-values, all correlations here are significant at the $p < 0.05$ level.

related to market capitalization and trading volume; it may be noted that a lower A-C score implies greater liquidity. All correlations are significant at $p < 0.05$ level (Exhibit 2).

To understand the impact that each variable has on the liquidity score, we estimated the following OLS regression model Equation (1):

$$eLS_i = a + \beta_1 \ln(BA_i) + \beta_2 \ln(S_i) + \beta_3 \ln(ER_i) + \beta_4 \ln(V_i) \ \forall i = 1, 2, \ldots\ 462 \tag{1}$$

where the ETF's A-C liquidity score (*eLS*, the estimated liquidity score in the regression) is the dependent variable and the factor variables are bid–ask spread (*BA*), size (*S*), expense ratio (*ER*), and three-month average trading volume (*V*)—each of them with the natural logarithm transformation; for each ETF *i* in our sample. The regression had an R^2 of 0.86, suggesting that our *eLS* value was reflecting well the unified influence of the four explanatory factors.[3] A low R^2 would have indicated a lack of monotonicity and an inability to aggregate the independent factors into an easily usable one-dimensional ranking score. Equation (2), provides the coefficient estimation results[4] along with the associated *p*-values.

$$eLS_i = \underset{(0.00)}{3.42} + \underset{(0.00)}{0.17}\ln\left(BA_i\right) - \underset{(0.08)}{0.02}\ln(S_i) + \underset{(0.00)}{0.13\ln(ER_i)} - \underset{(0.00)}{0.11\ln(V_i)} \tag{2}$$

These results indicate that the ETFs with low bid–ask spreads, high market capitalizations, low expense ratios, and high average trading volume produce the lowest numerical values that are also indicative of the highest liquidity levels. The signs on the coefficients are stable when referenced to the results from the Agrrawal and Clark [2009] study.

LIQUIDITY RANKING RESULTS AND FACTOR TRANSITION MATRIX: 2009–2014

Once the ranking was established we deciled the liquidity vector and present the averages of the associated factors in Exhibit 3. The CAPM betas for each decile are also included. ETFs in decile 1 have an average beta less than 1.00 for both 2014 and 2009, this could possibly be due to a higher proportion (25% versus 12.6% overall) of bond and broad market ETFs in the most-liquid decile. These results show that the most-liquid funds typically have a lower bid–ask spread, a higher market capitalization, lower expense ratio, and higher average trading volume. The top decile ETFs in 2014 have about four times the average daily trading volume of the next decile and more than two times the market capitalization. In 2009, the top decile had more than twice the average daily trading volume of the next decile and more than four times the market capitalization. This suggests that institutional traders may be migrating to very liquid ETFs and that they focus on these top decile ETFs because they rapidly execute large positions and need to minimize liquidity risk and market impact. Ben-David et al. [2014] found a link between arbitrage activity and high-frequency trading (HFT), which would necessitate extremely high liquidity, which is available in decile 1 ETFs. The low liquidity deciles have ETFs with high bid–ask spreads, low market capitalization, low daily trading volumes, and expense ratios that are about four times higher than the average of the 50 most-liquid ETFs. This suggests that the market is efficient enough to recognize these undesirable features and trades tend to be thin with these ETFs.

The transition of factors can be seen in Exhibit 4. The last row in the exhibit indicates that bid–ask spreads and expense ratios have compressed, which is a good trend for investors. Asset size and trading volume have gone up which can be indicative of greater market participation in the ETF environment. The adoption of ETFs into asset allocation plans and as hedging devices seems to have gained a firmer footing than five years ago. The only variable of concern is the overall beta of the ETFs, which seems to have moved up more than 9% (from 1.002 in 2009 to 1.096 in 2014)[5]. This may diminish the diversification benefits of ETFs to investors if they do not factor in asset correlations while forming portfolios or may point toward a systematic increase in the total risk composition of ETFs. Why that may be the case is potentially a topic for additional research.

Exhibit 5 lists the 50 most-liquid ETFs based on the A-C liquidity ranking methodology. It can be seen that many of the well-known ETFs are ranked very highly by the liquidity scoring algorithm and are represented in the top 50 list. QQQ (NASDAQ 100) comes in at number 1, BND (Vanguard Total Bond) at number 2, DIA (the Dow) at number 6 and SPY (S&P 500 SPDRs) at number 10. Of the top 50 for the 2014 rankings, 29 were also in the top 50 in 2009 rank-

Exhibit 3

Average Deciled Values (2014 and 2009) for Each of the Determinants of Liquidity

Panel A: 2014 Data

Decile (2014)	Liquidity	Bid–Ask Spread (bps)	Market Capitalization	Morningstar Total Expense Ratio %	Avg. Volume (3-mo. trailing)	CAPM Beta
1	Most Liquid	1.51	11,800M	0.17%	4,073,440	0.997
2	—	2.80	5,600M	0.35%	1,147,330	0.980
3	—	3.34	2,800M	0.39%	345,158	1.124
4	—	5.28	839M	0.50%	409,521	1.131
5	—	7.08	625.1M	0.46%	115,976	0.965
6	—	8.16	444.5M	0.50%	80,923	1.035
7	—	11.05	376.4M	0.49%	73,531	1.186
8	—	16.43	174.2M	0.59%	40,302	1.202
9	—	20.78	101.3M	0.61%	15,798	1.134
10	Least Liquid	39.77	31.2M	0.66%	6,563	1.143
Averages	**2014 Data**	**7.08**	**625.1M**	**0.486%**	**132,358**	**1.096**

Panel B: 2009 Data

Decile (2009)	Liquidity	Bid–Ask Spread (bps)	Market Capitalization	Morningstar Total Expense Ratio %	Avg. Volume (3-mo. trailing)	CAPM Beta
1	Most Liquid	2.84	2,400M	0.20%	2,942,060	0.976
2	—	5.11	1,100M	0.35%	1,718,580	1.015
3	—	5.62	535.9M	0.48%	425,787	1.015
4	—	12.86	187.3M	0.58%	153,546	1.007
5	—	10.19	113.7M	0.48%	95,465	0.935
6	—	15.79	90.1M	0.58%	75,844	0.975
7	—	14.26	92.6M	0.50%	59,858	1.035
8	—	18.63	64.4M	0.58%	32,132	1.053
9	—	22.59	42.4M	0.58%	21,412	0.988
10	Least Liquid	24.99	29.2M	0.65%	21,084	0.982
Averages	**2009 Data**	**10.72**	**144.6M**	**0.503%**	**121,819**	**1.002**

Exhibit 4

Factor Transition Matrix (2014–2009) for the Determinants of Liquidity

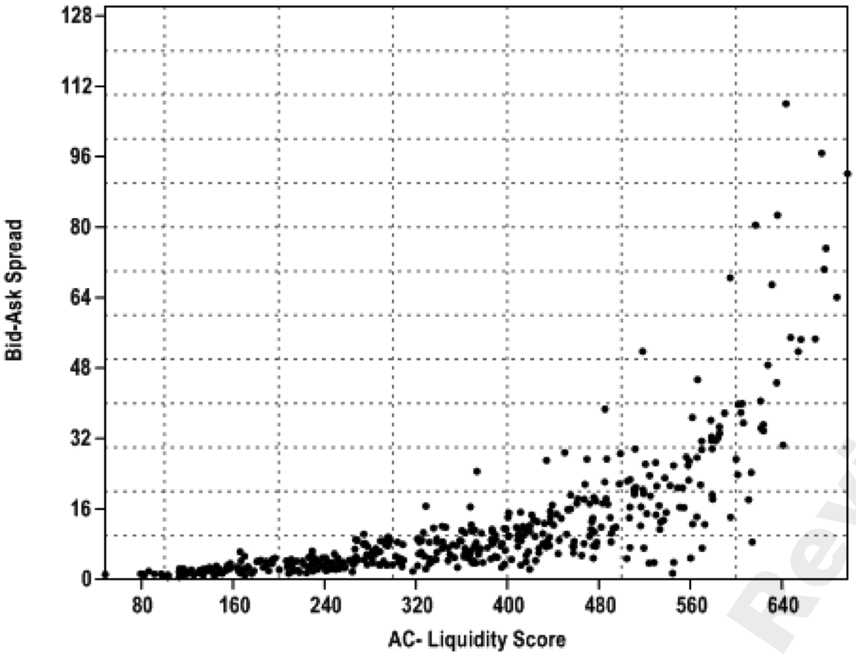
Transition (2014 Minus 2009)	Liquidity	Bid–Ask Spread (bps)	Market Capitalization	Morningstar Total Expense Ratio %	Avg. Volume (3-mo. trailing)	CAPM Beta
1	Most Liquid	–	+	–	+	+
2	—	–	+	–	–	–
3	—	–	+	–	–	+
4	—	–	+	–	+	+
5	—	–	+	–	+	+
6	—	–	+	–	+	+
7	—	–	+	–	+	+
8	—	–	+	+	+	+
9	—	–	+	+	–	+
10	Least Liquid	+	+	+	–	+
Overall	**2014 minus 2009 values**	–	+	–	+	+
Effect		**good**	**good**	**good**	**good**	**not good**

ings, indicating liquidity persistence among a majority of the established ETFs. Bond ETFs formed the majority of the new entrants into the top 50 group (2014 ranks).[6] It is also interesting to note that 48 out of the top 50 ETFs have at least $1 billion in market capitalization and 13 of the 50 ETFs are bonds, including 5 in the top 10. This increased visibility of fixed-income ETFs could be in response to the market crash in 2008, which resulted in

EXHIBIT 5
Top 50 Most-Liquid ETFs, 2014 Ranking

A-C Liquidity Rank	Ticker	ETF Name	BA Spread (Basis Points)	Trading Vol (3m):	Market Cap (million $)	CAPM Beta (vs. S&P 500)
1	QQQ	PowerShares QQQ	1.117	38,691,100	43,000	0.99
2	BND	Vanguard Total Bond Market ETF	1.238	2,204,400	110,800	***–0.05***
3	SHY	iShares Barclays 1–3 Year Treasury Bond	1.186	2,756,610	11,800	***0.00***
4	IWM	iShares Russell 2000 Index	0.845	43,888,200	27,000	1.29
5	AGG	iShares Barclays Aggregate Bond	1.861	1,272,490	15,900	***–0.05***
6	DIA	DIAMONDS Trust, Series 1	1.207	7,706,160	11,600	0.92
7	BSV	Vanguard Short–Term Bond ETF	1.251	1,085,070	35,200	0.01
8	TLT	iShares Barclays 20+ Year Treas Bond	0.930	7,667,410	3,100	***–0.81***
9	SHV	iShares Barclays Short Treasury Bond	0.907	717,402	2,600	***0.00***
10	SPY	SPDRs	0.529	112,813,000	158,100	1.00
11	IEF	iShares Barclays 7–10 Year Treasury	0.990	1,022,010	4,200	***–0.24***
12	IVV	iShares S&P 500 Index	0.525	5,416,570	50,000	1.00
13	IEI	iShares Barclays 3–7 Year Treasury Bond	1.664	1,556,370	6,300	***–0.06***
14	VWO	Vanguard Emerging Markets Stock ETF	2.444	19,727,100	56,300	1.40
15	HYG	iShares iBoxx $ High Yield Corporate Bd	1.063	4,289,080	13,500	0.51
16	IVW	iShares S&P 500 Growth Index	0.988	964,263	9,800	0.94
17	IWF	iShares Russell 1000 Growth Index	1.138	2,071,440	22,800	1.00
18	DXJ	WisdomTree Japan Total Dividend	2.080	6,771,440	12,000	0.77
19	JNK	SPDR Barclays Capital High Yield Bond	2.428	4,141,920	10,400	0.53
20	XRT	SPDR S&P Retail	1.153	3,579,810	993	1.18
21	IYR	iShares Dow Jones US Real Estate	1.468	10,566,100	4,400	0.89
22	VGK	Vanguard European Stock ETF	1.684	4,675,860	22,000	1.39
23	EWZ	iShares MSCI Brazil Index	2.169	17,691,700	4,100	1.64
24	XLE	Energy Select Sector SPDR	1.110	11,956,300	8,400	1.42
26	XLY	Consumer Discretionary SPDR	1.510	6,532,640	5,400	1.10
27	XLV	Health Care Select Sector SPDR	1.688	9,596,290	9,800	0.73
28	EFA	iShares MSCI EAFE Index	1.478	19,704,500	54,500	1.19
29	IWD	iShares Russell 1000 Value Index	2.056	1,739,300	20,800	1.04
30	XLI	Industrial Select Sector SPDR	1.881	11,477,900	9,000	1.10
31	BIL	SPDR Barclays Capital 1–3 Month T–Bill	2.185	669,803	1,000	***0.00***
32	IVE	iShares S&P 500 Value Index	2.284	535,906	6,400	1.06
33	TIP	iShares Barclays TIPS Bond	0.896	828,760	12,500	***–0.01***
34	MDY	MidCap SPDRs	1.969	2,403,120	15,900	1.18
35	VEA	Vanguard Europe Pacific ETF	2.403	3,480,110	23,400	1.20
36	XOP	SPDR S&P Oil & Gas Exploration & Prod	2.723	4,073,440	1,100	1.82
37	IWN	iShares Russell 2000 Value Index	1.952	1,073,610	5,800	1.25
38	EEM	iShares MSCI Emerging Markets Index	2.417	75,512,600	30,900	1.36
39	GLD	SPDR Gold Shares	0.808	7,989,290	34,200	0.37
40	XLB	Materials Select Sector SPDR	2.080	6,567,860	4,900	1.36
41	XHB	SPDR S&P Homebuilders	3.029	4,296,130	2,300	1.53
42	IWO	iShares Russell 2000 Growth Index	2.164	1,287,400	6,500	1.33
43	VTV	Vanguard Value ETF	1.269	736,866	28,800	1.00
44	LQD	iShares iBoxx $ Invest Grade Corp Bond	1.720	1,495,420	16,800	0.08
45	OIH	Oil Services HOLDRs	1.977	3,840,590	1,400	1.47
46	XME	SPDR S&P Metals & Mining	2.355	2,074,060	639	1.81
47	IJH	iShares S&P MidCap 400 Index	2.155	1,413,740	20,600	1.19
48	XLP	Consumer Staples Select Sector SPDR	2.323	9,496,030	5,600	0.56
49	CSJ	iShares Barclays 1–3 Year Credit Bond	1.900	791,879	13,400	0.05
50	SDY	SPDR S&P Dividend	1.349	753,676	12,500	0.78

EXHIBIT 6
Scatterplot of A-C Liquidity Scores vs. Bid–Ask Spreads for 2014



increased flows into fixed-income securities as a result of risk parity and optimization-based asset allocation strategies.

Nonetheless, bond ETFs typically get less media exposure, possibly due to a certain indifference toward non-equity securities and the persistent incorrect comparison charts on the Web that plot price-only returns of stocks versus bond ETFs, often resulting in performance ordering inversion and an "optical illusion" (Agrrawal and Borgman [2010]). This problem has been rectified by the Agrrawal and Agarwal [2012] procedure, which is also deployed in the CorrectCharts and ReturnFinder iApps that produce comparison total returns on the fly for individual securities as well as portfolios, besides providing portfolio stress-testing capabilities.

The non-linear positive relationship between the A-C liquidity score and the bid–ask spread is shown in Exhibit 6 (see the Appendix). Low A-C scores correspond to higher liquidity and are associated with lower B-A spreads on the underlying ETFs. Although there is greater dispersion toward the upper end of the B-A spreads, they are almost always associated with poor ETF liquidity. Creation/redemption units may partially offset the negative impacts of low trading volume and high bid–ask spreads on ETF liquidity, but the additional delay in trade execution time is another factor that could limit the interest of traders in such an illiquid security.

CONCLUSION

Using a set of factors commonly thought to impact liquidity, we develop a four-factor liquidity scoring algorithm, extending the Agrrawal and Clark [2009] algorithm, that allows us to rank the 462 ETF dataset from most liquid (#1) to least liquid (#462). The most-liquid funds typically have lower bid–ask spreads, higher market capitalizations, lower expense ratios, and higher average trading volumes. It can also be concluded that low-liquidity ETFs seem to have larger bid–ask spreads, typically smaller market capitalizations, higher expense ratios, and much lower investor interest (volume). Although low-liquidity ETFs may provide the investor with exposure to very narrow market segments (such as nuclear power, rare earth metals, social media or solar power, and so on), the costs of trading, market price impact, and ease of entering or exiting a sizable position must be carefully evaluated before initiating holdings in such ETFs. A market efficiency argument can also be invoked, which would support avoiding low-liquidity ETFs, especially when highly liquid, low-cost ETFs are readily available.

We also discovered that there is a very active bond ETF market as evidenced by the fact that 5 of the top 10 ETFs in our 462 ETF dataset are based on bond indexes.[7] Strategies such as risk parity, downside optimization (Kale [2006]), and multi-asset allocation models (Agrrawal [2009]) in the post-2008 crash period may be a contributory factor toward increased investor interest in bond ETFs.

The evolution of ETF liquidity over the 2009 to 2014 period was a central theme of this article, as well.

We find that there is liquidity persistence and factor strengthening across all variables. We find that the four liquidity factors have improved for the most liquid funds in the last five years, but they have worsened for the least liquid funds. Bid–ask spreads and expense ratios have compressed, which is a good trend for investors, and asset size and trading volume have gone up, which can be indicative of greater market participation in the ETF environment,[8] which is also good. The adoption of ETFs into asset allocation plans and as hedging devices seems to have contributed to asset growth. The class of ETFs has witnessed a phenomenal 34.9% annual growth rate, compared with a 19.8% annual growth rate in the Russell 3000, a 4.5% growth in the Lehman Aggregate Bond Index over the 2009–2014 time period (inflation was 1.86% a year over the period, aggregate market cap for our ETF dataset was $438 billion in January 2009 and $2,112 billion in April 2014, for the same set of ETFs). The ETF ecosystem seems to be thriving as the new asset class of choice among both institutional and retail investors.

However, there are two findings of concern. First, the overall beta of the ETFs in our study seems to have transitioned over time and moved up more than 9% (from 1.002 in 2009 to 1.096 in 2014).[9] This may be due to increased cross-asset correlations, sector intertwining, global market co-integration, or overlapping core constituents in ETFs, or simply because of a systematic upward drift in overall market risk premium. This increase could potentially diminish the diversification benefits of ETFs to investors if they do not factor in the asset covariance matrix while forming portfolios. Second, in the year 2009, we had a total of 622 ETFs for which we had bid–ask price data, of those only 462 remained in 2014, indicating a steep 25.7% closure rate for the low-liquidity ETFs (for this study, however, the same 462 were mapped to the 2009 ETFs for the associated factor values). This is an additional risk that investors and regulators have to keep in mind when investing in new entrants or evaluating low-liquidity ETFs. Although there was a total of about 884 ETFs in 2009, the number grew to about 1,595 in 2014. In such a populous environment, it is all the more important that investors and traders operate over the most liquid spectrum of the ETF landscape. The cost is often in the form of poor market depth, high expense ratios, and a range of trade execution difficulties, such as price impact and time delays, besides potentially high tracking errors with the associated benchmark index. Naturally, this cost is borne by the trader-investor.

In conclusion, we have reasons to think that ETF liquidity has significantly grown over time for most assets, that there is some natural pruning with pockets of concern, and that overall, ETFs have rapidly become a viable and efficient instrument in the asset management landscape. The ETF ecosystem, just like any other, has to be researched and managed for sustainable growth; whether market forces are sufficient for that purpose, only time will tell.

Appendix

LIQUIDITY RANKING ALGORITHM[10]

Our ranking algorithm (Agrrawal and Clark [2009]) determines a liquidity score and eventually a rank, for each of the 462 ETFs that have complete data for all four factors. An iterative optimization approach is utilized to obtain the factor loadings on each factor that contributes to a unified liquidity scalar score. The liquidity score vector is then transformed to an ordinal ranking for the full set of ETFs in our study.

$$\begin{aligned}
&Max\ \rho\left\langle \sum_{i=1}^{4} \omega_i^{\nu}\phi_i^{j}, \phi_{A\in\{1,..4\ factors\}} \right\rangle \forall\ j \in \{set\ of\ all\ ETFs\} \\
&\text{and } \forall\ \omega^{\nu} \in \{-\infty, +\infty\}\ and\ all\ \upsilon\ iterationss \\
&\xrightarrow{for\ optimal\ \omega^{*}} \sum_{i=1}^{4} \omega_i^{\nu}\phi_i^{j} \equiv eLS,\ the\ liquidity\ score \Rightarrow \Theta,\ the\ liquidity\ rank
\end{aligned} \tag{A-1}$$

Where ω are the weights on the ranked factors ϕ. Also Θ is the resulting rank of the liquidity score vector for the optimal ω^*, ρ is the correlation between the score array and the factor array, with the first factor ϕ_1 being the bid–ask spread. ϕ is the vector of "ranked factors," and in this case there are four factors (listed in Exhibit1). eLS is the regression model notation for the multifactorial A-C liquidity score. The first factor ϕ_1 is the bid–ask spread on each ETF, which is well known in the literature as a proxy for liquidity. So, think of ϕ_1 as a 462×1 column vector where each element is the bid–ask spread on the corresponding ETF. The iteration is to determine the weights for each of the four factors; hence ϕ_A, which thus constitutes the set of four column vectors, one each for each of the four factors. Eventually, we maximize the correlation ρ between *eLS*, the sumproduct of each row in a 462×4 matrix with an initially unknown set of weights $\{w_1 \ldots w_4\}$ and the column vector ϕ_1. The Excel Solver can be used to change each ω in the $\{w_1 \ldots w_4\}$ row vector to find an optimal set that maximizes the correlation between the bid–ask spread and the eLS score (which is a multivariate construct of the four factors, termed the A-C liquidity score). So, this gives us a weighted sum product of the four factors as a unified column vector of eLS [462×1]. Note that because ω^* is any real number, the iterations can be many, so we speed it up by limiting the increment to an integer and then dividing by 100 before we link it back to our sumproduct. The raw factors are also converted to an ordinal ranking of factors during the optimization process.

ENDNOTES

The article has benefited from discussions with Robert Strong, Ivan Manev, and John Mahon at the University of Maine; Tom Downs and Benton Gup at the University of Alabama; Satya Pradhuman of Cirrus Research, New York; Dan Dibartolomeo of Northfield Information Services, Boston; and Tanja Leber-Agrrawal for editorial assistance; their support is gratefully acknowledged. All errors and omissions remain those of the authors.

[1]Inflation was 1.86% a year over the period (see BLS.gov).

[2]There were 884 ETFs in 2009 compared with 1,595 ETFs in 2014 (Kosnett [2008], Investment Company Institute [2008], and ETFdb.com). Of those, 622 ETFs met our $1 million market-cap cutoff in 2009, by the year 2014 only 462 of them were trading, an attrition of 25.7%.

[3]This R^2 compares well with the 0.89 value in the Agrrawal and Clark [2009] study and indicates factor stability over time; it may also be noted that "turnover" was found to be not very explanatory in that study.

[4]All factors have been log-normalized.

[5]The set of ETFs for 2009 and 2014 was *exactly the same*, their liquidity rankings however changed. So this upward drift of beta cannot be attributed to fewer bonds or a higher proportion of sector or leveraged equity ETFs in 2014.

[6]Of the 622 ETFs that we had bid–ask data for in 2009, only 462 remained in 2014, indicating a steep 25.7% closure rate for the low liquidity ETFs. This is an additional risk that investors and regulators have to keep in mind while investing in new entrants or evaluating low liquidity ETFs. There were about a total of 884 ETFs in 2009, the number grew to 1,595 in 2014. Not all of them constitute the most-liquid spectrum of the ETF landscape. The cost is often in the form of poor market depth, high expense ratios, and a range of trade execution difficulties, such as price impact and time delays, besides potentially high tracking errors with the associated benchmark index.

[7]About 25% of the most liquid ETFs in our top 50 list and 12.6% of the 462 ETFs in our contiguous dataset are based on bond indexes.

[8]Ben-David et al. [2014] found a link between arbitrage activity and high-frequency trading, which could also be a contributory factor toward increased liquidity.

[9]The upward drift of beta cannot be attributed to fewer bonds or a higher proportion of sector or leveraged equity ETFs, because the set of ETFs was exactly the same in 2009 and 2014.

[10]The algorithm is made available for personal, informational, and educational use only, any commercial use would fall under the usage and licensing stipulations of Cloud Epsilon LLC.

REFERENCES

Agrrawal, P. "Using Index ETFs for Multi-Asset-Class Investing: Shifting the Efficient Frontier Up." *The Journal of Index Investing*, Vol. 4. No. 2 (Fall 2013), pp. 83-94.

——. "An Automation Algorithm for Harvesting Capital Market Information from the Web." *Managerial Finance*, Vol. 35, No. 5 (2009), pp. 427-438.

Agrrawal, P., and R. Agarwal. "CorrectCharts iApp." Library of Congress Copyright, Washington, D.C. DOI:LOC: 8-2012 Patent: TXu 1-838-163 (2012), http://correctcharts.com.

Agrrawal, P., and R. Borgman, "What Is Wrong with This Picture? A Problem with Comparative Return Plots on Finance Websites and a Bias against Income Generating Assets." *Journal of Behavioral Finance*, Vol. 11, No. 4, (2010), pp. 195-210.

Agrrawal, P., and J.M. Clark. "Determinants of ETF Liquidity in the Secondary Market: A Five-Factor Ranking Algorithm." *ETF and Indexing*, Vol. 43, No. 7 (2009), pp. 59-66.

Amihud, Y., and H. Mendelson. "Dealership Market." *Journal of Financial Economics*, Vol. 8, No. 1 (March 1980), pp. 31-53.

Ben-David, I., and F. Franzoni, and R. Moussawi. "Do ETFs Increase Volatility?" AFA 2013 San Diego Meetings Paper; Fisher College of Business Working paper No. 2011-03-20; Swiss Finance Institute Research Paper No. 11-66, April 2014. Available at http://ssrn.com/abstract=1967599.

Borkovec, M., and V. Serbin. "Create or Buy: A Comparative Analysis of Liquidity and Transaction Costs for Selected US ETFs." *The Journal of Portfolio Management*, Vol. 39, No. 4 (2013), pp. 118-131.

Chordia, T., R. Roll, and A. Subrahmanyam. "Liquidity and Market Efficiency." *Journal of Financial Economics*, Vol. 87, No. 2 (February 2008), pp. 249-268.

Garbade, K.D., and W. Silber. "Best Execution in Securities Markets: An Application of Signaling and Agency Theory." *Journal of Finance*, Vol. 37, No. 2 (May 1982), pp. 493-504.

Giulianini, P. "Understanding ETF Trading and Liquidity in Europe." *ETFs and Indexing*, (2012), pp. 81-86.

Hassine, M., and T. Roncalli. "Measuring Performance of Exchange Traded Funds." *The Journal of Index Investing*, Vol. 4, No. 3 (2013), pp. 57-85.

Investment Company Institute. "Exchange Traded Fund Assets." November 2008. Available at www.ici.org/stats/etf/.

Kale, J.K. "Growth Optimization with Downside Protection: A New Paradigm for Portfolio Selection." *Journal of Behavioral Finance*, Vol. 7, No 1 (2006), pp. 146-150.

Kale, J.K., and A. Sheth. "Power-Log Optimization for Maximizing Portfolio Growth and Controlling Tail Risk - An Empirical Study." Working paper, School of Economics and Business Administration, Saint Mary's College of California, 2013.

Kittsley, D., and J. Edrosolan. "Looking Inside Liquidity: An ETF Trading Case Study." *Institutional Investors Guide to Exchange Traded Funds*, (Fall 2008), pp. 32-36.

Kosnett, J.R. "Getting Past the ETF Clutter." *Kiplinger's Personal Finance*, Vol. 62, No. 9 (September 2008), pp. 32-35.

Krause, T., S. Ehsani, and D. Lien. "Exchange Traded Funds, Liquidity, and Market Volatility." Midwest Finance Association 2013 Annual Meeting Paper, January 11, 2013. Available at http://ssrn.com/abstract=2153903.

Kyle, A.S. "Continuous Auctions and Insider Trading." *Econometrica*, Vol. 53, No. 6 (November 1985), pp. 1315-1335.

Ryan, T.F., and J. Follet. "Are ETFs Liquid Securities?" *Institutional Investors Guide to Exchange Traded Funds*, (Fall 2001), pp. 106-110.

Stoll, H.R., and R.E. Whaley. "Transaction Costs and the Small Firm Effect." *Journal of Financial Economics*, Vol. 12, No. 1 (June 1983), pp. 57-79.

Waggle, D., and P. Agrrawal. "The Stock-REIT Relationship and Optimal Asset Allocations." *Journal of Real Estate Portfolio Management*, Vol. 12, No. 3, (2006), pp. 209-221.

Xiong, J.X., and T.M. Idzorek. "The Impact of Skewness and Fat Tails on the Asset Allocation Decision." *Financial Analysts Journal*, Vol. 67, No. 2 (2011), pp. 23-35.

Yan, X. "Liquidity, Investment Style, and the Relation Between Fund Size and Fund Performance." *Journal of Financial and Quantitative Analysis*, Vol. 43, No. 3 (September 2008). pp. 741-767.

Yu, S., and G. Webb. "The Effects of ETF Splits on Returns, Liquidity, and Individual Investors." *Managerial Finance*, Vol. 35, No. 9 (2009), pp. 754-771.