

LIQUIDITY IN EUROPEAN EQUITY ETFs: WHAT REALLY MATTERS?

■ INTRODUCTION



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ETFs are one of the major and most successful financial innovations over the past 20 years. Since the inception of the SPDR on the AMEX in 1993, the market for ETFs has experienced dramatic growth in terms of listed instruments, number of providers, assets under management (AuM), trading volume, investment styles and types of replicated assets among others¹. ETFs have become increasingly popular alternatives to conventional index mutual funds, introducing a new competing investment vehicle, rather than perfectly substituting for their conventional counterparts (Agapova, 2011; Guedj and Huang, 2009). One feature that has made ETFs strong competitors to mutual funds is their ability to provide efficient intraday exposure to an index at low cost as ETFs need not trade the underlying assets when facing demands for creation and redemption. According to Guedj and Huang (2009), this could explain why, in the case of indices exhibiting high volatility, illiquidity or industry concentration ETFs should on average perform better than mutual funds.

Despite the importance ETFs have recently gained, little is known about their liquidity. The academic literature initially focused on their performance and their impact on associated instruments such as index constituents, index derivatives and competing index mutual funds. The industry, when promoting ETFs, often argues that liquidity in ETFs is a simple matter that does not deserve much attention: the right measure for the liquidity of an ETF is the liquidity of the basket of stocks constituting the benchmark index. Although the role of other factors such as the trading volume is sometimes acknowledged, in the end, it is the immediate access to the liquidity of the underlying that really matters.

Understanding the liquidity of ETFs is of prime importance to answer various questions raised by the development of this market. ETFs now serve a variety of purposes,

including hedging and arbitrage. Liquidity is crucial for the efficiency of these operations (Deville and Riva, 2007; Ben David et al., 2011). Initially small in comparison to the stocks they hold, ETFs have significantly increased in terms of AuM and trading volume. They also cover a broader universe of stock baskets including small, exotic and infrequently-traded assets. As these ETFs represent a larger – and in some cases significant – proportion of the market value and trading volume of the underlying stocks, it may become problematic for market makers to act as liquidity providers in all circumstances.

The aim of our paper is to provide evidence of the determinants of the spreads in the European equity ETF markets from their inception in 2000 to the end of 2011. Although the European markets share most of the characteristics of US markets, these markets deserve specific analysis due to some notable differences, in legal structure and fragmentation, for example. Using a comprehensive sample of European equity ETFs, we relate the size of ETF spreads to the liquidity of the benchmark index, but also to variables known to be determinants of the spread and to variables associated with the characteristics of the ETF, including but not restricted to the replication technique and the investment style. Our first explanatory variable is the liquidity of the benchmark index as measured by the spread of the underlying stock basket. Actually, the alleged capacity of ETFs to build on the liquidity of their benchmark indices relies on their specific open-ended structure. This structure aims at permitting direct arbitrage between the ETFs and the underlying stock basket, which in turn ensures efficient pricing of ETFs. It can also be used by market makers facing orders exceeding the normal capacity of the ETF market: they can always provide liquidity by trading the underlying basket and, as authorized participants (APs), by creating or redeeming shares at their Net Asset Value. The industry thus claims that, the more liquid the benchmark index, the more efficient the liquidity provision by market makers, even for small and new ETFs or when there is little trading volume on the ETF secondary market.

To our knowledge, this argument, though theoretically sound, has not been empirically tested on a large sample

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of ETFs. It is true that blue chip ETFs generally present tighter spreads compared to those of ETFs replicating small-cap indices. However, several empirical observations cast doubt on this argument. Hougan (2008) computes average spreads of NYSE-listed ETFs for the first months of 2008. He finds that ETFs tracking the same index often display very different levels of spreads. On Euronext Paris, the ETFs competing for the replication of the CAC 40 index trading on Euronext Paris initially displayed spreads that could vary threefold. Competition itself may also impact the size of spreads. For the CAC 40 ETFs, the introduction of two competitors (EasyETF CAC 40 and Amundi ETF CAC 40) in March 2005 after 4 years of monopoly for Lyxor CAC 40 ETFs resulted in a significant decrease in the spreads of the incumbent.

Another argument for the need for a deeper look at the process of liquidity provision relies on the specificities of the European ETF market. In Europe, the development of more exotic underlying indices combined with a more liberal regulation soon called for synthetic replication based on total return swaps. In such synthetic ETFs, the fund does not hold the underlying securities of the benchmark index. It enters into a total return swap by which the counterparty commits to delivering the exact index return in exchange for the effective performance of the ETF holdings and a fee. The development of these new replication structures has been accompanied by the possibility of creation and redemption in cash: instead of the underlying stock basket, APs can ask for the creation of shares against cash or even futures. For synthetic ETFs we may thus find a weaker link between the liquidity of the ETF and that of its benchmark index².

In general, "liquidity is an elusive concept" (Amihud, 2002). Its measurement is difficult due to the different dimensions it encompasses. This is particularly true for ETF markets where (i) shares can be created or redeemed to absorb liquidity shocks, and (ii) the available data is of relatively poor quality. Measuring liquidity in European ETFs is even more challenging as the order flow for an ETF is often fragmented among different trading venues and OTC trades are generally not reported³. We restrict our attention to a simple but effective measure of liquidity, the closing spread. We consider that it represents a robust, though noisy, indicator of the liquidity provided by market-makers. Although investors may trade off-exchange, spreads are a visible way through which ETFs can demonstrate liquidity. In addition, despite the alleged capacity of any ETF to raise liquidity, investors still prefer more heavily traded ETFs. As liquidity begets liquidity, spreads are of particular importance to issuers in competition with other issuers and to markets that compete for the order flow.

On our sample of European equity ETFs, we find that ETF closing spreads are significantly associated with the liquidity of the underlying index, but that this relationship is not very powerful. Accounting for conventional determinants of the spreads in equity markets, we are able to significantly improve the model fit. Contrary to the classic argument, it appears that the ETF size matters: larger and more heavily traded ETFs display tighter spreads. Finally, we show that microstructure issues are

also of prime importance. Competition among ETFs and fragmentation among listings impact the liquidity displayed in ETF markets. We then test whether the relationship holds in sub-samples and find that the liquidity of physical and synthetic ETFs are both affected by the crisis but in opposite ways; a result that we explain by transfers of investors from one category to the other. Finally, we show that the relationship, though significant, is weaker for synthetic and sector ETFs. The provision of liquidity of these ETFs is thus partly driven by factors unaccounted for in our model.

Related studies focus on how the advent of ETFs impacts the trading and market quality of index component stocks. Building on the theoretical work addressing the impact of the introduction of index futures (Subrahmanyam (1991), Fremault (1991)), Hedge and McDermott (2004) compare measures of information asymmetry on the underlying stocks before and after the ETF starts trading and also investigate which of the ETF or its underlying stock basket displays the highest liquidity. Overall, they find that, in the case of the Diamonds and Cubes (two well-known ETFs tracking the DJIA and the NASDAQ 100 index, respectively), the ETF attracts very little informed trading and is more liquid than the individual stock basket.

Although very insightful about the possible impact of the introduction of ETFs, these studies address the question for a very limited number of ETFs trading on US exchanges, and focus on a very limited time period around their introduction. Hamm (2010) investigates the effect of the introduction of ETFs on the liquidity of individual stocks with a large dataset of US equity ETFs. She finds a positive relationship between the availability of ETFs and the adverse selection component of underlying stocks' bid-ask spreads. However, this liquidity effect is in turn transferred to the ETFs, thus reducing the benefit of switching to ETFs for liquidity traders.

The papers of Ben-David *et al.* (2011) and Petajisto (2011) are also related to liquidity in ETFs, though in a more distant way. Ben-David *et al.* (2011) use data on ETFs traded on the major US exchanges to assess the role of arbitrage in the propagation of liquidity shocks between ETFs and the underlying stocks. They provide evidence of mispricing in the ETF market and relate it to measures of limits to arbitrage, among which spreads appear specifically significant. Furthermore, they show that arbitrage activity takes place between ETFs and their underlying securities and that it is tightly connected to ETF mispricing. As a result of this arbitrage activity, liquidity shocks can spill over to the underlying assets, increasing volatility and correlations. Petajisto (2011) also highlights the importance of the underlying (and funding) liquidity in the arbitrage activity to exploit the pricing inefficiencies in US ETFs.

The rest of the paper proceeds as follows. Section 1 explains how the ETF-specific trading structure links the liquidity of ETFs with the liquidity of the stocks constituting the benchmark index. Section 2 describes our sample of ETFs and the variables we use in the regressions. Section 3 shows evidence that the liquidity of an ETF depends on the liquidity of its underlying index but is also determined by other factors. Section 4 concludes.

I. MEASURING THE LIQUIDITY OF ETFs

A widespread opinion among practitioners is that the liquidity of an ETF is determined by the liquidity of the underlying index. The reason for this presumed dependence comes from the open-ended feature of ETFs and from the structure they traditionally use to achieve their replication objective, i.e. physical replication. In this structure, ETF APs (who may also make the market for the ETF) deliver the constituent stocks of the replicated index to the ETF sponsor in exchange for ETF creation units to be traded on the ETF secondary market. Providing liquidity to a large buy order on the ETF secondary market thus implies the creation of new ETF units, which involves the purchase of the corresponding basket on the stock market. Conversely, any market maker holding a large inventory of ETF shares can redeem them against the stock basket at their Net Asset Value. Arguably, the APs will reflect in their ETF quoted spread the implicit costs borne when trading the basket shares, and illiquidity on the stock market will smear over the ETF liquidity.

However, alternative structures, known as synthetic replication, may loosen this kind of relationship. Among these structures, the most popular involves the use of a total return swap, whereby the ETF sponsor receives the total return of the index for a given nominal exposure, and the cash provided to the swap counterparty is invested in a basket of collateral assets that is transferred to the ETF sponsor. In this replication scheme, authorized participants are generally provided with ETF creation units in exchange for cash instead of the underlying index basket, with the effect of separating ETF liquidity from that of the index constituent stocks.

Measuring liquidity is a difficult task and involves the use of various proxies aimed at capturing liquidity across its various dimensions (immediacy and price impact). Since we use daily data, we restrict our choice to three widely used low-frequency liquidity estimators: the relative quoted spread, the Roll estimator of the effective spread⁴ and the Amihud illiquidity ratio⁵. We use all three measures in turn to compute the underlying basket liquidity. These proxies present some interesting advantages among which the most important is that they are easy to compute even on markets for which the availability of accurate data is questionable. Their computation only involves closing spreads (relative quoted spread), closing prices (Roll effective spread) and daily trading volume (Amihud illiquidity measure). Despite their simplicity, they are shown to perform well in effectively measuring the liquidity in equity markets (Goyenko, 2009). As to ETF liquidity, we only use a relative quoted spread measure as in Ben-David *et al.* (2011). It turns out that the other two measures, which are based on asset returns are irrelevant in the case of ETFs, whose returns mainly reflect those of the benchmark index. Indeed, it can be shown that both the Roll estimator and the Amihud ratio are in fact indirect ways to capture the tracking error of an ETF and are only weakly related to its liquidity⁶.

For both stocks and ETFs, we use closing data that smooth out any intraday changes and may not be representative of the market conditions faced by investors trading before the close or OTC. Another possibility is to build daily measures by averaging intraday spreads as in Hassine and Roncalli (2013). However, relying on closing spreads is the easiest way of capturing liquidity even on markets where the quality of data is unreliable. This is of particular importance here as we work with ETFs trading on 19 different exchanges replicating indices with 8,668 different constituent stocks trading on 81 exchanges over the world. Moreover, as found with closing data, McInish and Wood (1992) demonstrate that the behavior of equity spreads measured intradaily can also be explained by variables measuring activity, competition, risk, and information.

For each ETF and each basket, we construct monthly time series of liquidity measures. The liquidity of a given ETF for a given month is computed as the average of its relative closing quoted spreads over that month. To compute the liquidity of a basket on a given month based on the spread and Amihud measures, we proceed as follows. Following Chordia *et al.* (2011), we compute each day the equally-weighted⁷ average of individual constituent stock measures. When a stock does not trade (or has missing information) on a given day, we rescale the weights of the remaining constituent stocks on a pro rata basis to keep the sum of the weights always equal to one. The daily averages are then averaged over the month to produce the liquidity estimate of the basket for that month. In the case of the Roll estimate of the basket effective spread, we first compute the associated Roll from the autocovariance of stock returns over that month for each stock within a basket. The individual Roll estimates (one per month) are then averaged to compute the liquidity of the basket. If the Roll estimator of a stock is not available for a given month⁸ weights are rescaled on a pro rata basis.

II. DATA DESCRIPTION AND SUMMARY STATISTICS

We use BlackRock's ETF Landscape Global Handbook (2011) to identify ETFs traded on European exchanges. This document is a directory of all 4,152 Exchange Traded Products (ETPs) listed around the world, as at the end of October 2011. For each equity-ETF, we gather the following information: product name and Bloomberg ticker, benchmark index, type of asset class exposure (broad, region, sector and/or strategy), total expense ratio (TER), dividend policy, legal structure, issuer, primary market with listing date and listing date on other exchanges for cross-listed ETFs.

Our primary interest lies in the links existing between the ETF and the index through its constituent stocks. We thus select the ETFs tracking indifferently the price index, the total return index or the equally-weighted index, as long as they all share the same component stocks. We extract from Bloomberg the daily time series of the composition of these indices (from 2 January 2002

to 4 November 2011), which allows us to build the list of all the component stocks over the period.

We work with a sample of 346 ETFs (1,122 listings) listed on 19 different European markets, replicating 204 different indices, and issued by 27 issuers. A few large issuers (iShares, Lyxor, DBX) dominate the market, in terms of number of ETFs and AuM. Issuers are highly specialized in terms of replication style but most offer both types of ETFs, which is probably due to specific advantages offered by each technique. Overall, synthetic ETFs are preferred on emerging indices while physical ETFs dominate national and regional indices. Figure 1 depicts the evolution of our sample, between 2000 and 2011, in terms of number of ETFs. Although the European market was initially dominated by physical ETFs, upcoming issuers mainly listed synthetic ETFs.

Table 1 reports the description of our ETF sample by replication style (physical or synthetic), as of the end of 2011. We divide the sample according to the type of asset class exposure (broad, sector, regional or single country) and to the geographical area (global, developed, emerging). Synthetic ETFs account for 64% of the total number of ETFs but only for 36% of the total AuM. Almost all types of indices have both synthetic and physical ETFs. Although physical replication can be used to replicate emerging market or sector indices, synthetic ETFs dominate these index types (both in terms of number of ETFs and AuM). The proportion of physical ETFs is higher only for developed/regional indices. For developed market indices, synthetic ETFs dominate in terms of number of ETFs but physical ETFs dominate in terms of AuM. Cross-listing is the rule in European equity ETFs: most ETFs trade on multiple exchanges either for physical ETFs (78%) or synthetic ETFs (68%). Most ETFs replicate indices for which a futures contract exists, but for an approximate 20%, there is no corresponding futures contract and it should be noted that most futures contracts were introduced after the ETF has initially been listed.

These features of our sample also hold for the whole market. Our sample represents 43% of the European Equity ETF market in terms of number of ETFs and 64% in terms of AuM. Among the ETFs for which we do not have the time-series of index composition, MSCI indices, that are excluded from the sample due to the unavailability of composition data, account for 67.5% of the number (86% of AuM). Only 5 very small issuers and a few small ETFs are not represented in our sample. The proportions of physical vs. synthetic are qualitatively similar between the whole market and our final sample (39% vs. 36% physical on the number of ETFs, 60% vs. 64% physical on AuM).

To construct our liquidity measures for ETFs and their benchmark indices and the other explanatory variables, we extract the following variables from Bloomberg: for both stocks and ETFs we take high, low, opening and closing prices, closing bid-ask spreads, traded volume and turnover, and for ETFs we complement these measures with the fund net asset value (NAV) and the number of shares. We use daily observations to construct monthly averages. The dependent variable in our regressions is the ETF closing bid-ask spread. Other ETF liquidity variables

are the trading volume (in shares and USD) and the AuM (computed as the shares outstanding multiplied by NAV). For cross-listed ETFs, we distinguish the trading volume observed on the primary listing exchange from the total volume traded over all listings. These variables are highly correlated and will be used in turn as alternative measures of size in our regressions.

As for index variables we use equally-weighted averages of individual measures calculated at the stock level. Beside the liquidity measures described in Section 1 (quoted spread, Roll effective spread and Amihud ratio), we include the daily index volatility (standard deviation) and three variables aiming at measuring the size of the benchmark index: the number and average market value of constituents stocks and the total market value of the index.

We include in our regressions variables related to the ETF market environment: the number of markets where the ETF is listed (cross-listings), the normalized Herfindahl index of market fragmentation⁹ and the number of competing ETFs on a given index. We also include monthly dummy variables indicating whether a futures contract on the same index exists in that month, if the ETF and the index do not trade in the same currency (currency risk) or time zone (asynchronicity) or whether or not the observed period is during the financial crisis (2008-2009)¹⁰. To account for differences in market structure, we include market indicator dummies as control variables. Finally, we include variables related to ETF characteristics: a dummy variable for the replication style indicates whether the ETF uses physical or synthetic replication techniques and takes on the value 1 for synthetic and 0 for physical ETFs; as a proxy for the type of asset class, we use a dummy that takes on value 1 for ETFs that replicate a sector index and 0 for non-sector indices (broad, national or regional). To improve the quality of data and avoid extremely noisy observations, we discard the first month of data as well as the ETFs that have less than one year of data available.

Table 2 reports summary statistics for the variables that are used in our regressions. ETF liquidity variables are characterized by large variances, with a few very large spreads, trading volumes and AuM pushing up the average values of these variables. Averages are always higher than medians suggesting that a significant proportion of our sample is composed of thinly-traded ETFs characterized by large closing spreads. The same feature is observed for the closing spread of the underlying baskets and the market value. As shown by the large dispersion of index market values, ETFs track a wide range of indices in terms of size (benchmark index market value), liquidity (as measured by the basket closing spread, effective spread and Amihud measure) and size (average market value of underlying stocks) and number of constituent stocks. Though the market is not very competitive with an average of 3.8 ETFs replicating the same benchmark, some indices attract up to 21 competing ETFs. The order flow faces additional fragmentation coming from the different listings of the same ETF. On average, an ETF is listed on 3 different exchanges, but ETFs on popular indices such as the EuroStoxx 50 can count up to 12 listings. Effective fragmentation of the trading volume, as measured by the

Herfindahl Index indicates that in most cases, with an average of 0.70, one listing is dominant. Restricting our attention to cross-listed ETFs, we observe a significant degree of fragmentation, with an average value of 0.59.

Table 3 reports summary statistics for liquidity variables by style. The first two columns compare all physical and synthetic ETFs. The rest of the Table reports results for physical and synthetic ETFs by benchmark type: developed vs. emerging and global (cols 3-6) and national and regional vs. sector (cols 7-10). Like for the full sample, the most salient feature of the first two columns is the high heterogeneity of our universe of ETFs. This diversity is likely to hinder the univariate comparisons between means and medians across replication styles: physical ETFs exhibit lower average closing spreads but higher median closing spreads. The tight link that is claimed to exist between ETF liquidity and index liquidity seems to show up when we split the sample into style categories which are *a priori* reflective of the difficulty of replicating the index. ETF spreads are significantly tighter for developed and non-sector ETFs, as opposed to those replicating emerging, global and sector indices.

The comparison between physical and synthetic ETFs yields no clear conclusion. Mean and median tests of the difference in spread size produce different rankings of the performance of the replication techniques. However, this univariate analysis does not account for the heterogeneity in the index selection, in the prevailing trading environment for the ETF and in the global market conditions. In the next section, we control for these factors in a multivariate setting.

■ III. MULTIVARIATE ANALYSIS

In this section, we investigate the links existing between the liquidity of the ETFs and their underlying index, as well as the impact of other variables related to ETF characteristics, to the structure of the market, as well as to the benchmark index and its constituent stocks. Figure 2 depicts the evolution of the distribution of the relative quoted spreads of the ETFs and their underlying baskets over the sample period. With a few exceptions, the relative quoted spread of the ETFs is larger than the spread of the underlying baskets. Overall, the cross-sectional variance of ETF spreads decreases over time and the gap between ETF spreads and underlying basket spreads tends to shrink even though new ETFs replicating more exotic indices enter the market. As expected, the market turmoil starting in 2008 results in a sharp increase in the spreads both for the overall stock market and the ETF market. To explore the determinants of the spread of ETFs and its link with the benchmark spreads in a multivariate setting, we run OLS regressions with standard errors clustered by index benchmark and year-month (Petersen, 2009).

III.1. THE DETERMINANTS OF THE SPREAD

Table 4 reports the determinants of the liquidity of ETFs for the full sample. In model 1, we regress the relative

quoted spread of the ETF against the equally-weighted quoted spread of the index. Consistent with the claim that the ETF liquidity is that of its underlying index, we do find a significantly positive relationship between the two variables¹¹. However, the spread of the basket only explain 13% of the variance in ETF spreads. Model 2 includes additional variables that are known to be classic determinants of the spread in equity markets (Stoll, 2000). As in equity markets, the size of the spread decreases with the ETF trading volume¹² and increases with the benchmark index volatility. This is at odds with the index liquidity argument since more heavily traded ETFs exhibit lower spreads. Yet, the liquidity of the underlying basket remains a significant determinant of the spread. To account for the heterogeneity evidenced in Table 3, we include in model 3 the type of replication and the investment style of the index. We find that synthetic ETFs exhibit spreads lower than those of physical ETFs by 1 basis point and that ETFs that replicate sector indices have spreads higher than others by 3 basis points. This result is a bit surprising: sector indices are but subsets of broader liquid indices; their replication thus should not raise any specific issue. As seen in Table 3, sector ETFs, as niche products, are small funds in terms of AuM. Although size is accounted for through the trading volume variable, a threshold effect may explain why liquidity is deteriorating in sector ETFs. We investigate more extensively the effects of the replication style and of the benchmark type in Table 5.

In model 4, we introduce all the other variables that can possibly impact the provision of liquidity in ETF markets. These variables are related to the issues of the competition among ETFs and/or market places or to additional difficulties in the replication of the index. Fragmentation is associated with higher spreads for cross-listed ETFs: the spread decreases with the order flow concentration on the primary listing. Fragmentation of the order flow between ETFs competing on the same benchmark index has the opposite effect of tightening the spread. When these variables are accounted for, the replication style loses significance. Hence, the replication style per se does not appear to provide additional liquidity and the tighter spreads observed on synthetic ETFs are rather due to the increased competition they face. The size of the index and its constituent stocks (index total market value and average constituent stock market value) do not seem to have any additional effect that would not already be accounted for in their spreads. To account for other risk factors we also include risk-related indicators. Surprisingly, we find no evidence of significant differences in spreads whether a futures contract exists on the same index or not, or if the ETF and the index do not trade in the same currency or time zone. A positive, slightly significant coefficient for the dummy variable indicating whether or not the observed period is during the financial crisis (2008-2009), suggests that spreads increased during the crisis not only because of the higher volatility but also in connection with some other factors affecting the market making at these times. In all our regressions we have also included market indicators to control for the impact of market-related characteristics: the market on which the ETF is listed explains an important proportion of the variance.

Overall, in the European equity ETF market, we evidence multiple determinants of closing spreads, among which the liquidity of the benchmark index remains prevalent. The explanatory power of our model remains modest for the complete model with an adjusted R^2 of 18.42%. We investigate in the next sub-section whether all types of ETFs are equally affected by market conditions.¹³

III.2. DETERMINANTS BY REPLICATION TECHNIQUE AND INVESTMENT STYLE

Given the relevance of the distinction between synthetic and physical ETFs and between sector and non-sector ETFs, we further explore ETF liquidity relationships by dividing our sample according to the replication style and benchmark type. Table 5 compares the regression coefficients across these sub-samples. The most striking and distinctive feature is that the link between ETFs and their benchmark seems to loosen for synthetic ETFs (cols 1-2): unlike their physical counterparts, synthetic ETFs spreads are not significantly affected by the benchmark's size and liquidity. The index size has a positive impact on the spreads for physical ETFs, suggesting that the larger the benchmark, the more difficult to trade this class of ETFs. Contrary to physical ETFs, for which we have a good quality of fit (R^2 of 47%), synthetic ETFs are only very partially explained by the model (R^2 of 14%). Like for the full sample (Table 4), both synthetic and physical ETFs spreads decrease with the ETF trading volume and increase with the benchmark index volatility.

A surprising result is that, while the financial crisis (2008-2009) undermines the liquidity of the full sample (see Table 4, model 4) and of synthetic ETFs (Table 5, col 2), it tightens physical ETF spreads. A possible explanation is the massive outflow of liquidity from the synthetic ETFs, due to the controversy over the risks presented by synthetic replication. Part of this liquidity probably shifted to physical ETFs, thereby increasing their liquidity and generating the observed positive impact of the crisis that we find in our data. This hypothesis is confirmed by the evolution of AuM during the crisis: while AuM globally decreased in 2008 and 2009 (from 794 million USD in 2007 to 779 million USD in 2009, to increase again in 2010 up to 830 million USD), when we compare the two replication subsets, we find that the AuM largely decreased for swaps (from 338 million USD in 2007 to 203 million USD in 2009) but increased for physical ETFs (from 457 million USD in 2007 to 576 million USD in 2009). When we replace the trading volume by the AuM in our subset regression, we observe that the quality of fit improves remarkably for physical ETFs (with an R^2 of 61%) and the crisis loses its significance. The other coefficients are not affected by the use of AuM. For the sake of comparison with the full sample model, we do not include AuM in the model in Table 5.

A puzzling result is the opposite effect of market concentration: the size of spreads increases with concentration for physical ETFs while it decreases for synthetic ETFs. Possible explanations may relate to the distinctive features of physical and synthetic ETFs. In the case of physical ETFs, we have a high average index of concentration for

cross-listed ETFs (Herfindahl = 0.72). Fragmentation, at moderate levels, is generally associated with higher liquidity, (Degryse 2013; O'Hara and Ye, 2012). Conversely, for synthetic ETFs, we find a higher degree of fragmentation for cross-listed ETFs (Herfindahl = 0.44). This important fragmentation may deteriorate market liquidity (Degryse, 2013).

The second part of Table 5 reports the results of the comparison between sector and national/regional ETFs. A few specificities of these subsets relative to the full sample described in Table 4 must be noted: trading fragmentation reduces the liquidity of sector ETFs (spreads decrease with trading concentration) but does not affect the other ETFs, while the number of competing ETFs on the same index enhances liquidity only for non-sector ETFs; both are negatively correlated with the existence of a futures contract on the same index; only sector ETFs seem to be affected by the crisis (with an associated increase in spreads) and by the replication type (spreads are higher for physical ETFs). However, with an R^2 of 15%, the model explains only a small proportion of sector spread.

Given the striking heterogeneity of our universe of ETFs, we finally test the robustness of our findings by restricting the analysis to the European country ETFs (last column of Table 5). This represents a more homogeneous sample with highly liquid benchmark indices composed of blue-chip stocks. Even for these highly liquid indices, we find that spreads are determined by factors other than the liquidity of the underlying benchmark: the main results are similar to those obtained for the physical ETFs (col. 1), except that the index size is not significant, as was the case for the full sample. The quality of fit is slightly improved, compared to the full sample, but poorer than that obtained for the physical ETFs, confirming our findings that the heterogeneity in the spreads of synthetic ETFs is only partially explained by our models.

IV. CONCLUSION

We explore the determinants of ETF liquidity using a large sample of European funds. We first test the validity of the widespread opinion according to which there is strict mapping between the liquidity of an ETF and that of its underlying basket. Though those two quantities are significantly and positively correlated, the liquidity of the basket explains but a modest 13% of the variance of ETF spreads. Including variables that are known to be determinants of stock spreads, we find that the liquidity of ETFs is negatively correlated with their trading volume and positively correlated with the volatility of their underlying basket. Accounting for additional variables aimed at capturing the specific feature of ETFs, we find that ETFs replicating sector indices exhibit higher spreads. This result is somehow puzzling as sector indices are generally liquid subsets of blue-chip indices. We also find that synthetic ETFs exhibit lower spreads than physical ETFs. However the replication dummy loses significance once we include the number of ETFs competing on the same index. Since synthetic ETFs operate on competitive

markets, this result suggests both that the higher spreads we document on physical ETFs have a monopoly rent flavor and that the replication technique per se is not a determinant of liquidity. ETFs exhibit higher spreads during the crisis. Since we control for volatility, this finding implies that other factors that lead to a deterioration in ETF liquidity are at work during the crisis. This is particularly true for synthetic ETFs. A possible explanation is that the synthetic structure of these instruments and the controversy on their alleged counterparty risk may have acted as a deterrent to potential investors. Actually, we find that, compared to physical ETFs, synthetic ETFs are those which have experienced the most significant outflows during the crisis.

This paper is a first step in the understanding of liquidity provision in ETFs. As with any empirical study, a few caveats should be mentioned. First, the liquidity proxy we use in this paper, following Ben-David *et al.* (2011), is a relative quoted spread measure based on closing data. Though robust, closing spreads are noisy measures of liquidity. The use of intraday spread data, as in Hassine and Roncalli (2013), could be a step towards building daily measures that are more representative of the market conditions prevailing throughout the day. Second, this study focuses on exchange trading though a large proportion of the turnover occurs OTC. However, as long as these trades are not consistently reported, overall liquidity cannot be estimated more accurately. Finally, the use of intraday data would allow for a detailed analysis of the microstructure of ETF markets. In particular, the issues of fragmentation and competition, which are shown to affect spreads, deserve additional analysis.

ACKNOWLEDGEMENTS

This research has benefitted from the support of the Amundi ETF “Core-Satellite and ETF Investment” research chair at EDHEC-Risk Institute. The authors are grateful for helpful comments from Bruno Biais, Marie Brière (editor) and the referee. We also thank seminar participants at Toulouse University and conference participants at the 6th CSDA International Conference on Computational and Financial Econometrics for comments and suggestions. We thank Erika Richter for providing the data. Fabrice Riva gratefully acknowledges the support of the QUANTVALLEY/FdR “Quantitative Management Initiative”. ■

- 1 According to Blackrock May 2011 Report, the global ETF industry had 2,747 ETFs with 6,079 listings and assets under management of US\$ 1,446.6 Bn, from 142 providers on 49 exchanges around the world. This compares to 2,218 ETFs with 4,411 listings and assets of US\$ 1,044.1 Bn from 131 providers on 42 exchanges at the end of May 2010.
- 2 Although synthetic ETFs may not hold the index basket, they engage in a total return swap to track the index return. The swap counterparty that pays the index return in exchange for the ETF portfolio's return is likely to hedge his risks by taking position on the index stock basket either directly or through index futures, when available. In terms of counterparty risk, Amenc *et al.* (2012) show that there is no significant difference between the two types of ETFs. Both are exposed to limited and regulated counterparty risk: when synthetic ETFs enter in OTC total return swaps, physical ETFs resort to securities lending to improve their performance.
- 3 Under current MiFID legislation, there is no obligation to report off-exchange trades for ETFs. The obligation to report these trades in ETFs to build a so-called consolidated tape and improve post-trade transparency has been proposed in the revisions to MiFID II, which is currently in the consultation phase.
- 4 The Roll estimator of the spread is a simple implicit measure of the effective cost of trades based on the autocovariance of returns. Denoting r_t the return at date t , the expression of the relative effective spread is given by $2\sqrt{-\text{cov}(r_t, r_{t-1})}$.
- 5 The Amihud illiquidity ratio is defined as $|r_t|/V_t$, where r_t is the return at date t and V_t is the corresponding dollar trading volume. Intuitively, the higher the Amihud ratio the lower the liquidity since a low trading volume gives rise to a large price impact.
- 6 As to the Roll estimator of the effective spread of an ETF, we show that the estimator mainly builds upon the benchmark index autocorrelation of returns rather than on the ETF's own liquidity characteristics. Proof is available from the authors upon request.
- 7 Chordia *et al.* (2001) show in their analysis of market liquidity and trading activity that value-weighted and equally-weighted measures lead to qualitatively unchanged results. We check whether this remains valid in the case of ETFs by running our regressions with a value-weighted measure on a sub-sample of indices for which constituent weights are available. In that case, we use the weights reported in Bloomberg for the last trading day of the month.
- 8 To avoid representativeness issues, any stock having less than 12 returns in a given month is excluded from the Roll computations for that month.
- 9 The Herfindahl index is a measure of market concentration. Based on the (squared) market share of each listing, it measures the fragmentation of the trading volume in an ETF across all the exchanges where it is listed. For N ETFs, it varies between $1/N$ (perfect competition) and 1 (in the case of a monopoly). The normalized Herfindahl index we use in this paper varies between 0 and 1.
- 10 These dummies take on the value 1, respectively, when a futures contract exists, when the ETFs and the index do not trade in the same currency, when they trade in different time zones, when the observed month is in the period 2008-2009; and 0 otherwise.
- 11 Although not reported in the paper, we obtain qualitatively similar results when we replace the index closing spread by the Roll effective spread. For the Amihud illiquidity measure, a measure of price impact, the coefficient of the Amihud measure, although positive, does not significantly affect the ETF quoted spread. Either price impact does not affect spread or this ratio does not accurately proxy liquidity in our case. Indeed, the Amihud ratio provides highly heterogeneous results when applied to stocks displaying structurally different levels of liquidity.
- 12 Trading volume is the USD total trading volume. Results in model 2 to 4 are qualitatively unchanged if the other measures of volume or the AuM of ETFs are used instead. However, given the high rate of missing values for the number of shares, the use of the AuM is costly in terms of sample size.
- 13 Our results could be affected by the choice of the sample. In a robustness test not reported for brevity and available upon request, we fit model 4 on the subset of ETFs trading on Xetra (the largest market in the sample). We also compare the regression coefficients obtained using either the equally-weighted or the value-weighted measures, for a subset of 46 indices for which we have the daily series of stock weights and are thus able to build both the equally-weighted and value-weighted measure. Finally, we re-run the regression on more recent periods as the early years may reflect an immature market and introduce noise in our estimates (cf. Figure 2). The results are qualitatively unchanged and the fit is similar to that reported in model 4 of Table 4 in all cases.

Figure 1. Evolution of equity ETFs in sample (2000 - 2011)

This figure depicts the evolution of the total number of ETFs in our sample between 2000 and 2011 and reports for each month the number of introductions of both synthetic (in grey) and physical (in black) ETFs.

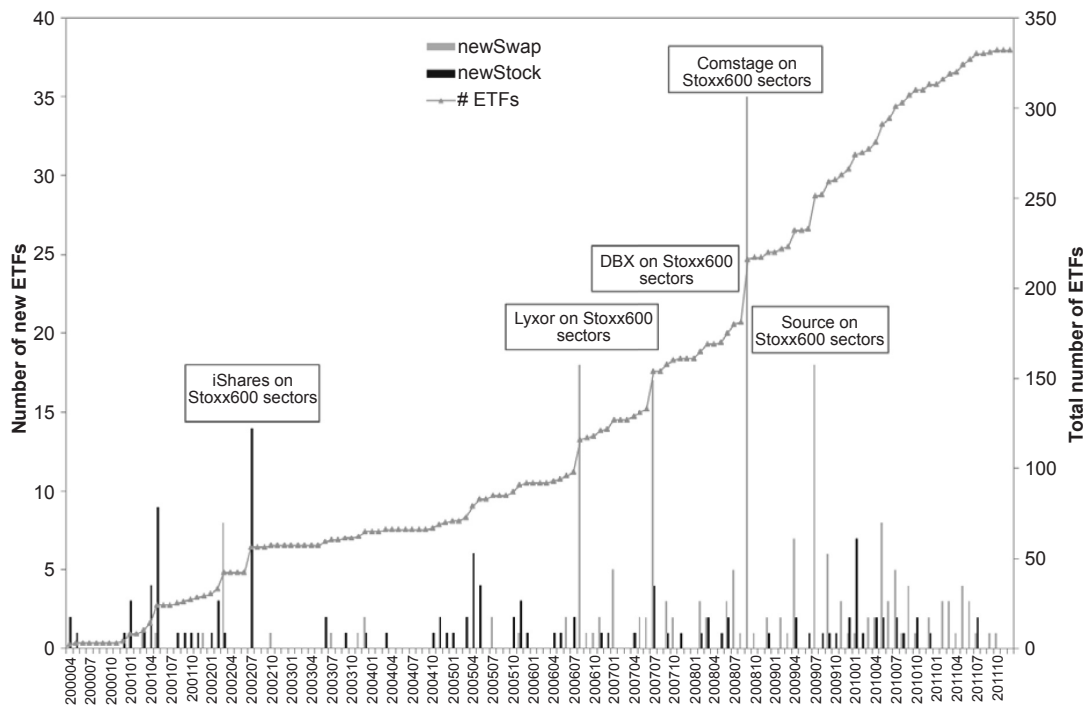


Figure 2. Evolution of the distribution of the relative quoted spreads of the ETFs and their underlying baskets over the sample period

This figure depicts the evolution of the distribution of the relative quoted spreads of ETFs and their underlying baskets over the period January 2001 - December 2011. The box and whiskers plots use the following conventions: the top and the bottom of the boxes are equal to the 75% and the 25% quantile, respectively; the length of the whiskers is equal to 1.5 times the value of the interquartile range. Dots represent the median value of the ETF relative quoted spread.

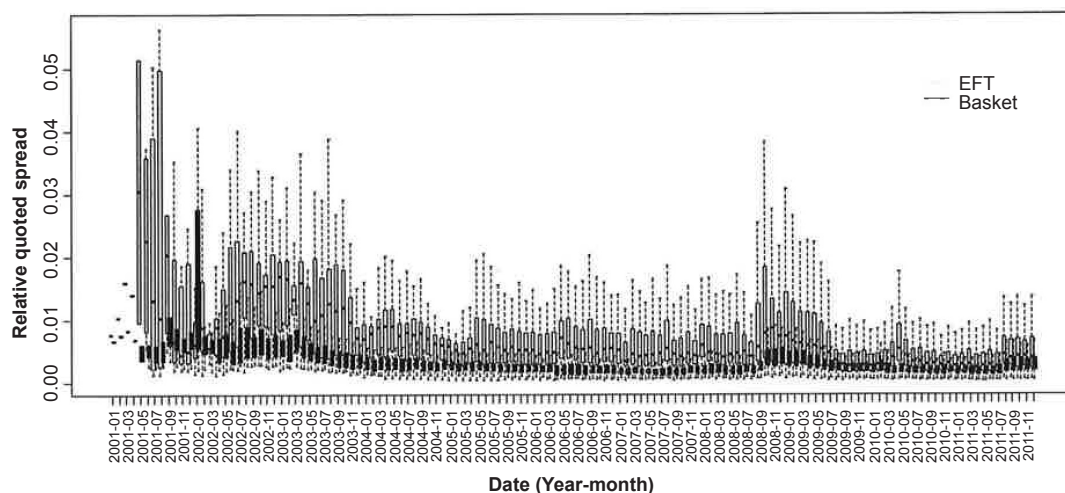


Table 1. ETF sample description by replication style

This table reports the summary characteristics of our sample of ETFs in terms of number of ETFs (# ETFs), number of listings (# Listings) and AuM (in US million dollars). Multi-offered reports the percentage of ETFs that are cross-listed and Futures reports the percentage of ETFs for which the benchmark index serves as an underlying asset for an exchange-traded futures contract. Statistics are computed by type of asset class exposure (Broad, Sector, Regional and Single country) and by geographical area (Developed, Emerging and Global).

	# ETFs		# Listings		Multi-offered (%)		AuM (US\$m)		Futures	
	Stocks	Swaps	Stocks	Swaps	Stocks	Swaps	Stocks	Swaps	Stocks	Swaps
Developed	110	185	357	578	81.82%	67.57%	8,021,095	4,006,080	90.00%	81.62%
Regional	32	26	141	85	90.63%	57.69%	1,782,418	1,175,480	84.38%	88.46%
Sector	22	82	60	250	100.00%	62.20%	194,737	608,190	100.00%	73.17%
Single country	56	77	156	243	69.64%	76.62%	6,043,940	2,222,410	89.29%	88.31%
Emerging	11	28	35	103	36.36%	71.43%	207,730	522,428	36.36%	57.14%
Regional	3	4	14	16	66.67%	100.00%	102,634	54,982	0.00%	0.00%
Sector	1	0	7	0	100.00%		11,215		0.00%	
Single country	7	24	14	87	14.29%	66.67%	93,881	467,446	57.14%	66.67%
Global	3	9	13	36	100.00%	77.78%	22,568	74,676	33.33%	11.11%
Broad	1	1	2	3	100.00%	100.00%	13,685	7,231	100.00%	100.00%
Sector	2	8	11	33	100.00%	75.00%	8,883	67,445	0.00%	0.00%
All	124	222	405	717	78.23%	68.47%	8,251,393	4,603,184	83.87%	75.68%

Table 2. Summary Statistics – Whole Sample

This table reports summary statistics on the trading characteristics of ETFs and their underlying baskets. Variables labeled Primary market report statistics on the trading characteristics of the ETFs on their primary market. Variables labeled All report statistics on the trading characteristics of ETFs based on data consolidated across the various trading venues of cross-listed ETFs. The trading volume concentration is computed from the normalized Herfindahl index on trading volume. Its value is comprised between 0 (ETFs competing on the same index have equal market shares) and 1 (the ETF replicating a given index has no competitor).

Variable	N	Mean	S.D.	Min	Median	Max
ETF closing spread	17,404	0.7847%	1.5496%	0.0257%	0.4231%	36.1032%
ETF monthly trading volume (shares) primary market	17,404	2,671,773	12,121,853	0	193,569	406,785,558
ETF monthly trading volume (shares) all markets	17,404	3,442,519	14,122,300	0	293,500	415,878,298
ETF monthly trading volume (US\$K) primary	17,404	82,463.72	321,837.40	0	8,779.42	7,859,713.70
ETF monthly trading volume (US\$K) all	17,404	106,890.08	377,600.83	0	13,082.39	8,033,502.51
ETF AuM (US\$ mn.)	15,128	353.17	1,212.47	0.29	67.18	87,103.78
Number of ETFs competing on the same benchmark	17,404	3.78	3.70	1	3.00	21.00
Number of listings	17,404	2.8739	1.8242	1	2	12
Trading volume concentration	17,381	0.7012	0.3392	0	0.8970	1
Number of stocks in benchmark	17,404	112	260	10	34	1955
Basket closing spread (equally weighted)	17,063	0.2894%	0.2664%	0.0278%	0.2202%	4.1700%
Basket effective spread (Roll's measure) (equally weighted)	17,404	1.6152%	0.7604%	0.3494%	1.3937%	7.5661%
Amihud (equally weighted)	17,404	0.7465%	0.7718%	0.0266%	0.5069%	8.6644%
Basket closing spread (value weighted)	5,383	0.2277%	0.2093%	0.0207%	0.1702%	2.2499%
Basket effective spread (Roll's measure) (value weighted)	5,593	1.5496%	0.7579%	0.4846%	1.3439%	6.4896%
Amihud (value weighted)	5,593	0.3373%	0.4655%	0.0416%	0.2055%	6.8197%
Average underlying stock market value (US\$ mn.)	17,312	18,089	18,721	350	13,497	147,468
Benchmark index market value (US\$ mn.)	17,312	1,206,051	1,762,223	9,593	511,968	13,920,548
Daily index volatility within the month (%)	17,403	0.0144	0.0088	0.0026	0.0119	0.1504

Table 3. Summary statistics – liquidity variables by style

This table reports the mean and the median of liquidity measures for ETFs and their underlying benchmark as well as the significance of the difference in means and medians between replication styles (Physical vs Synthetic replication), type of asset class exposures (National Regional vs Sector) and geographical area (Developed vs Emerging).

	Physical	Synthetic	Physical		Synthetic		Physical		Synthetic	
	All	All	Developed	Emerging Global	Developed	Emerging Global	National Regional	Sector	National Regional	Sector
ETF closing spread										
mean	0.6435%	0.9220%	0.5941%	1.2406%	0.8556%	1.2617%	0.7815%	0.5866%	0.7714%	1.0864%
t-test p-value	<0.001		<0.001		<0.001		<0.001		<0.001	
median	0.4294%	0.4151%	0.4074%	0.6267%	0.3559%	0.9426%	0.6854%	0.3350%	0.4426%	0.3894%
Wilcoxon p-value	0.0228		<0.001		<0.001		<0.001		0.4977	
ETF turnover (US\$ thousands)										
mean	132,282	80,535	137,294	71,767	86,362	50,688	181,037	14,243	139,360	16,291
t-test p-value	<0.001		<0.001		<0.001		<0.001		<0.001	
median	20,982	7,273	21,752	9,541	7,339	6,984	36,738	6,955	10,994	5,469
Wilcoxon p-value	<0.001		<0.001		0.0247		<0.001		<0.001	
Basket Closing spread(EW)										
mean	0.2954%	0.2832%	0.2764%	0.5203%	0.2579%	0.4178%	0.2834%	0.3237%	0.3262%	0.2382%
t-test p-value	0.0027		<0.001		<0.001		<0.001		<0.001	
median	0.2220%	0.2173%	0.2145%	0.3915%	0.2016%	0.3250%	0.2022%	0.2602%	0.2324%	0.2090%
Wilcoxon p-value	0.2026		<0.001		<0.001		<0.001		0.0423	
Avg constituent stock MV (US\$mn)										
mean	19,655	16,460	19,169	25,493	16,455	16,483	22,941	11,747	20,261	12,359
t-test p-value	<0.001		<0.001		0.9677		<0.001		<0.001	
median	15,095	11,813	15,543	7,705	13,391	8,948	18,029	10,343	12,386	11,623
Wilcoxon p-value	<0.001		<0.001		<0.001		<0.001		<0.001	

Table 4. Determinants of ETF spreads

This table reports OLS regression results of ETF spread determinants. Basket closing spread is the equally-weighted spread of the underlying index stocks; ETF trading volume is the USD trading volume of the ETF across all listings; Replication is a dummy variable that takes on the value 1 for synthetic ETFs and 0 for physical ETFs; SectorETF is a dummy variable that takes on the value 1 for ETFs offering exposure to a particular subset of a broader index and 0 otherwise; Fragmentation is the Herfindahl index for the concentration of trading volume: its value is comprised between 0 (ETFs competing on the same index have equal market shares) and 1 (one ETF fully dominates the market or has no competitor); Nb.cross-listings is the number of trading venues an ETF is listed on; Index.MV is the market value (in million USD) of the underlying index; Und. Stock avg.MV is the average market value (in million USD) of the underlying index constituent stocks; Crisis is a dummy variable that takes on the value 1 for data observed during the period 2008-2009 (financial crisis); Asyncho is a dummy variable that takes on the value 1 if the ETF trades in periods at which the market for all or part of the assets pertaining to its underlying index is closed; Currency risk is a dummy variable that takes on the value 1 if the ETF trades in a currency which is different from that of its underlying index; Futures is a dummy variable that takes on the value 1 if the ETF replicates a benchmark that serves as an underlying asset for a futures contract; Market dummies are dummy variables aimed at controlling for differences in the trading characteristics of the markets ETFs trade on. We report t-statistics based on clustered standard errors using a double clustering on both years and index benchmark. ***, ** and * denote significance at the 10%, 5% and 1% level, respectively.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.0007	0.0070**	0.0051*	0.0084***
t-stat	0.25	2.54	1.86	2.85
Basket closing spread (EW)	0.9299***	0.5876***	0.6310***	0.6267***
t-stat	4.28	2.54	4.04	3.54
ETF trading volume		-0.0007***	-0.0006***	-0.0006***
t-stat		-7.18	-5.99	-5.84
Index volatility		0.2936***	0.2907***	0.27***
t-stat		6.358	23.02	6.86
Replication			-0.0010***	-0.0010
t-stat			-4.01	-1.53
SectorETF			0.0031***	0.0034***
t-stat			12.47	3.42
Fragmentation				-0.0021**
t-stat				-2.18
Nb.cross-listings				0.0000
t-stat				0.10
Nb.compet.ETFs				-0.0002***
t-stat				-4.48
Index.MV				0.0002
t-stat				0.98
Und. Stock avg.MV				0.0000
t-stat				1.07
Crisis				0.0016**
t-stat				1.97
Asyncho				-0.0011
t-stat				-1.11
Currency.risk				0.0006
t-stat				0.56
Futures				0.0006
t-stat				0.77
Market dummies	Yes	Yes	Yes	Yes
N. obs.	17 063	17 063	17 063	17 031
R-squared	0.1326	0.1690	0.1771	0.1857
Adj. R-squared	0.1316	0.1680	0.1761	0.1842

Table 5. Determinants ETFs spreads by style

This table reports OLS regression results of ETF spread determinants. Basket closing spread is the equally-weighted spread of the underlying index stocks; ETF trading volume is the USD trading volume of the ETF across all listings; Replication is a dummy variable that takes on the value 1 for synthetic ETFs and 0 for physical ETFs; SectorETF is a dummy variable that takes on the value 1 for ETFs offering exposure to a particular subset of a broader index and 0 otherwise; Fragmentation is the Herfindahl index for the concentration of trading volume: its value is comprised between 0 (ETFs competing on the same index have equal market shares) and 1 (one ETF fully dominates the market or has no competitor); Nb.cross-listings is the number of trading venues an ETF is listed on; Index.MV is the market value (in million USD) of the underlying index; Und. Stock avg.MV is the average market value (in million USD) of the underlying index constituent stocks; Crisis is a dummy variable that takes on the value 1 for data observed during the period 2008-2009 (financial crisis); Asynchro is a dummy variable that takes on the value 1 if the ETF trades in periods at which the market for all or part of the assets pertaining to its underlying index is closed; Currency risk is a dummy variable that takes on the value 1 if the ETF trades in a currency which is different from that of its underlying index; Futures is a dummy variable that takes on the value 1 if the ETF replicates a benchmark that serves as an underlying asset for a futures contract; Market dummies are dummy variables aimed at controlling for differences in the trading characteristics of the markets ETFs trade on. We report t-statistics based on clustered standard errors using a double clustering on both years and index benchmark. ***, ** and * denote significance at the 10%, 5% and 1% level, respectively.

	Replication style		Benchmark type		European country ETFs
	Stocks	Swaps	Sector	Other	
Intercept	0.0076**	0.0179***	0.0331***	0.0089***	0.0067**
t-stat	2.30	4.12	5.99	3.03	2.56
Basket closingspread (EW)	0.6008**	0.3203	0.8457**	0.4675***	0.3476*
t-stat	2.55	1.62	2.30	2.64	1.83
ETF trading volume	-0.0007***	-0.0006***	-0.0006***	-0.0006***	-0.0003***
t-stat	-6.07	-4.48	-3.45	-4.83	-3.81
Index volatility	0.1488***	0.3930***	0.3678***	0.2098***	0.1577***
t-stat	5.16	5.59	6.16	7.05	4.05
Replication			-0.0082***	0.0008	0.0000
t-stat			-4.23	1.53	0.08
SectorETF	0.0024***	0.0030**			
t-stat	3.31	2.11			
Fragmentation	0.0030***	-0.0034***	-0.0029*	0.0007	0.0013*
t-stat	4.63	-2.72	-1.70	0.87	1.92
Nb.cross-listings	0.0003	0.0001	0.0013	0.0001	0.0002
t-stat	1.26	0.39	1.52	0.38	0.91
Nb.compet.ETFs	-0.0003***	-0.0001	-0.0004	-0.0003***	-0.0004***
t-stat	-6.43	-0.73	-0.89	-6.07	-3.88
Index.MV	0.0007***	-0.0002	-0.0011	0.0002	0.0011
t-stat	5.38	-0.74	-1.07	1.52	1.52
Und. Stock avg.MV	0.0000	0.0000	0.0000	0.0000	0.0000
t-stat	1.15	0.21	-0.33	1.24	0.34
Crisis	-0.0010**	0.0045***	0.0047***	0.0001	-0.0009*
t-stat	-2.04	3.12	2.88	0.22	-1.82
Asynchro	-0.0023***	-0.0004	-0.0052	-0.0005	
t-stat	-2.72	-0.24	-1.43	-0.54	
Currency.risk	0.0016**	-0.0005		0.0006	0.0031***
t-stat	2.18	-0.27		0.55	7.87
Futures	-0.0019***	-0.0009	-0.0055*	-0.0019**	0.0012
t-stat	-2.62	-0.82	-1.84	-2.01	0.85

Table 5. (suite)

Marketdummies	Yes	Yes	Yes	Yes	Yes
N. obs.	8696	8335	6655	10376	3956
R-squared	0.4723	0.1411	0.1541	0.3347	0.2295
Adj. R-squared	0.4707	0.1390	0.1522	0.3327	0.2250

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