The Impact of Multilateral Trading Facilities on Price Discovery:
Further Evidence from the European Markets

Mike Buckle

University of Liverpool,

Chatham Street, Liverpool L69 7ZH, UK

Jing Chen

Cardiff University,

Senghennydd Road, Cardiff CF24 4AG, UK

Qian Guo

Birkbeck College, University of London,

London WC1E 7HU, UK

Xiaoxi Li (corresponding author)

University of Swansea,

Singleton Park, Swansea SA2 8PP, UK

Email: dr.xiaoxli@outlook.com   Tel: +44 (0) 01792 205678

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Abstract

This study examines relative price discovery for three major European indices, FTSE, CAC, and DAX, their futures and exchange traded funds (ETFs) using the data on 5-minute intraday transaction prices over a four-year period. We computed both Hasbrouck (1995) information share with error bounds and Gonzalo and Granger's (1995) common factor weights approach. Gonzalo and Granger's (1995) common factor weights suggest the index futures contracts play a dominant role in price discovery in the CAC market: the CAC 40 index futures lead the price discovery and Lyxor CAC 40 ETFs serving the second resort for information transmission. This could be due to the less frequent trading of ETFs. More importantly, CAC40 under the Gonzalo & Granger (1995) test shows upper and lower error bounds in good range may be the main reason to drive for the meaningful results. In contrast, the upper and lower bounds estimated from the Hasbrouck (1995) are far distant for most cases. Finally, FTSE and DAX markets offer compelling evidence to show that ETFs lead price discovery and spots and futures follows.

Keywords: Exchange Traded Funds; Price Discovery; Information Share; Common Factor Weights

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1 Introduction

Nearly a decade after the financial crisis in 2008, exchange traded funds (ETFs) have become highly active and has resumed its significance in the financial market, especially its price discovery function. This is primarily due to their nature as highly flexible multilateral trading facilities, which enable diversification and hedging, and eventually effective and efficient investment decisions for economic agents. One example of this emerged during the Fukushima nuclear disaster in 2011. While the home market in Tokyo was shut down, the Japanese ETFs listed in the U. S. continued to trade.[1] Consequently, it eased investors' tension and reversed their tremendous potential loss through adjusting investment portfolios in response to alterations in this disaster of radioactive leak.

In Europe, the demand for ETFs has never been higher as witnessed presently, and European ETFs tend to be multilateral traded simultaneously in London, Frankfurt, and Paris. Compared to mutual funds, ETFs have clearly become more preferred investments because it is flexible,

extremely liquid, low-cost and offers pricing transparency. According to ETFGI, a London-based independent research and consultancy firm, ETFs managed in Europe reached a record high of US$571 billon[2] at the end of 2016. A year later, this value amounted to as high as US$777 billon, increased by a record US$206 billion approximately.[3,4] BlackRock predicts European ETFs under management will reach the amount US$1000 billion by the end of 2020. Currently, European ETFs are largely owned by institutional investors and retail investors' adoption of ETFs is a crucial ingredient that is still missing.[5]

The European ETF market entails a highly fragmented market with multiple trading venues and listings. According to ETFGI, at the end of December 2016, there were 6,976 listings from 56 ETF providers across 25 exchanges in 21 countries. The main European ETFs such as DAX, Euro Stoxx 50, Italy's MIB, France's CAC 40, and the pan-European STOXX 50 index operate in some of the most liquid markets. Given the current boom and major growth in ETF trading in Europe, the need for research addressing the impact of the introduction of new instruments on the existing price discovery structure is urgent.

Recent academic literature on price discovery seem to have little concentration on the emergence of new financial instruments of this kind (see, for example, Stoll and Whaley, 1990; Chan, 1992; Choi and Subrahmanyam, 1994; Fleming et al., 1996; Shyy et al., 1996; Pizzi et al., 1998; Chu et al., 1999; Theissen, 2012). The majority have focused on the role of price discovery between futures and spot markets and the general consensus is that futures market often dominates.[6] The traditional view of the lead and lag type of studies suggest that the strong price discovery among financial assets is rooted in three basic aspects: low trading costs (e.g. Fleming et al., 1996; Chan, 1992), risk diversification (Subrahmanyam, 1991; Gammil & Perold, 1989; Deville et al., 2014) and sufficiency together with synchronization of trading (Stoll & Whaley, 1990; Chan, 1992; Shyy et al., 1996; Chou and Chung, 2006; Theissen, 2012). ETFs, which are designed to replicate the performance of an index as closely as possible (Hedge and McDermott, 2004) through a single instrument/fund of a basket of securities, demonstrate excellence in all these areas. However, literature show varied results that stock futures still overpower ETFs in many cases. For instance, Frommherz (2017) argues that futures and ETFs of DAX are found in a contesting relationship: the stock index futures market still takes the lead and it was closely followed by the ETF; but the level of dominance of futures

was weakened by the ETFs contribution to price discovery. Additionally, trading of the ETF

led to the close alignment of share prices of the underlying components of DAX. This means

the price gap between the ETFs and underlying stocks were tightened more than that between

spot and futures.[7,8] Therefore, the important and natural question to ask is whether proliferation

of ETFs change the existing price leadership held by the stock index futures markets

universally or it is subject to a specific market? Again, according to Madhavan and Sobczyk

(2016), there is no simple answer exists to the question of whether ETFs or index futures

present the more cost-efficient alternative. This is because either can be characterized by factors

such as short- and long-term investments as well as fully-funded and leveraged investments.

However, Deville et al. (2014) asserted that ETFs attract long-term position hedgers and

liquidity traders, and hence, ETFs proliferation may result in the redistribution of index traders

across the index markets, which, in turn, can enhance the price efficiency.

After the extensive investigation of the literature, we are urged to further study the role of ETFs

in price discovery. This issue is particularly significant and urgent as the recent proliferation

of ETFs may lead to changes in the existing price discovery structure. To accomplish the above-

sated purpose, we undertake an extensive study of price discovery for three major European

price indices, focusing on whether ETFs have surpassed futures or spot indices to become the

leading information transmission vehicle. In particular, we examine three major European

stock market indices (FTSE 100 in UK, CAC 40 in France, and DAX 30 in Germany), their

futures and ETFs, using a large-scale dataset covering 4 years of intraday 5-minute transaction

prices. Our paper employs the Hasbrouck (1995) information share and Gonzalo and Granger

(1995) common factor weights approaches to investigate the lead-lag relationship in price

discovery between the spot index, index futures, and ETFs. The common factor weights

analysis produced substantial evidence to support the view that the ETFs have taken over

futures contract and currently form the dominant vehicle for price discovery, especially in the

UK and German stock markets. Index futures contracts play a significant leading role in the

price discovery process in the French stock market, primarily due to the lower trading

frequency of ETFs in the CAC index market.

The major contributions of our study are summarized below. The literature presents an

acceptable body of studies for the examination of the role of spots and futures or spots and

ETFs in price discovery. However, so far, there have been only two studies that examined the way in which the dynamics change, if all three asset classes are considered (see Ivanov et al., 2013; and Chou and Chung, 2006). Therefore, the need for studies such as ours for enriching the literature is more urgent. We were successful in answering the question with regard to the instrument that acts as the price leader in a substantial way. In terms of the methodology, our research is among the few studies that have employed different methods to offer a robust examination of the question related to price discovery; most studies use merely one method. This allows us to present findings that are reliable in relation to the time period and methodology selected.

With regard to the findings of our study, we discovered that over time, ETFs have assumed dominance as a vehicle for price discovery in relation to the two main European stock market indices. This further presents findings that are contradictory to that of Hasbrouck (2003), Schlusche (2009), and Theissen (2012), while they are similar to the inferences made by Ivanov et al. (2013) and Chou and Chung (2006). However, our study is considerably more comprehensive compared to those of Ivanov et al. (2013) and Chou and Chung (2006).

Furthermore, this has been discussed in greater depth in Section 5.3 of the paper. The discovery of a greater role of ETFs in the price discovery process also contributes to the wider policy debate regarding their role in stock markets.

The remainder of this study is organized as follows: Section 2 offers a critical review of the existing literature; Sections 3 and 4 discuss the empirical data and research methodology employed for this paper, respectively; Section 5 presents the estimated results and findings; and Section 6 provides the conclusion to this study.

2 Literature Review

2.1 What Informational Role Do ETFs Play in Price Discovery? - Summary of Findings from the Literature

Several studies have investigated the contribution of ETFs in the price discovery process in relation to the trading costs hypothesis. Broadly, they suggested that although ETFs offer cheaper costs and have increased in terms of popularity and volume, their contribution to the phenomenon of price discovery is limited. For instance, Beaulieu et al. (2003) and Chou and

Chung (2006) examined the effects of the decimalization of ETFs trading on price discovery.[9]

Their results indicated that index futures continue to lead price discovery. More importantly,

ETFs began to gain a significant information share after the reduction of ETFs' trading costs,

reflecting their increasingly important role in price discovery.

However, Deville et al. (2014) examined the direct and indirect effect of ETFs on their

underlying stocks' price efficiency. The effect of ETFs on arbitrage activities in the spot and

futures markets is referred to as the direct effect of ETFs, while the effect of ETFs on the

respective underlying stocks' liquidity is described as the indirect effect of ETFs. While in the

short term, neither direct nor indirect effect of ETFs on the price efficiency of their component

stocks could be observed based on the data used in their study; however, Deville et al. (2014)

suggest that in the long term, the price efficiency improves, especially through the indirect

effect of ETFs.[10] They suggested that the ETFs are more appealing to hedgers and liquidity

traders who focus on long-term positions, but they may appear unattractive to arbitrageurs in

relation to index futures. This is because ETFs are traded at lesser frequencies than futures, and

arbitrageurs concerned with short-term profitability may prefer stocks and futures rather than ETFs.

Hasbrouck (2003) analyzed the dynamics of price discovery using both intraday quotes and trades for a wide range of market indices and related contracts including ETFs. The groups examined were the S&P 500, S&P Midcap 400, and NASDAQ-100, comprising regular floor-traded futures, E-mini futures, and SPDR ETFs, respectively. One of the main findings of his study was that for the S&P 500 and NASDAQ-100 indices, E-mini dominates the price discovery over spot indices, with the contract itself possessing the dominant information share that accounts for up to 90% of the price discovery. In this case, the paper found that in spite of the introduction of ETFs, futures still held the lead in terms of price discovery.

Tse et al. (2006) investigated both intraday quotes and trades across the Dow Jones and S&P 500 market indices and related contracts. The groups examined were the Dow group, comprising of the Dow Jones Industrial Average index (DJIA), electronically traded DJIA ETF (DIAMOND), floor-traded futures, and Dow E-mini, and the S&P group, including S&P 500

index, S&P futures (floor-traded), S&P E-mini, and SPDR ETFs. Their results suggest that for both groups, the electronically traded futures make the maximum contribution to the price discovery process, followed by ETFs and then indices.

Significantly, however, Ivanov et al. (2013) studied indices, index futures, and index ETFs across the DJIA, S&P 500, S&P 400, NASDAQ-100, and Russell 2000. Although the study was not conducted at the intraday level but at the daily level, it generated compelling evidence suggesting that the introduction of ETFs mitigates the index futures dominance in revealing the underlying price updating process. This result is compatible with that of Chou and Chung (2006), who observed that ETFs start to gain a significant information share.

Krause et al. (2014), on the other hand, analyzed the volatility spillover effect and asserted that there are volatility spillover flows from ETFs to their component stocks, a process in which volatility is a driving factor in price discovery.

2.2 Classical Methodologies Employed to Study the Price Discovery: An Evaluation of Their

Features and Drawbacks

2.2.1 Vector Autoregressive (VAR) Representation of the Data to Purge Infrequent Trade

Existing literature on the agents involved in price discovery has documented various empirical

methodologies to identify the contribution of a market to the process of price discovery. The

first branch of the literature focuses on the VECM or vector autoregressive (VAR)

representation of the data obtained from multivariate regression analyses. The central rationale

is to address the infrequent trade problems in stock index return, in order to allow index return

to be expressed as the weighted average of the contemporaneous and lagged returns along with

an error disturbance component, with the assumption that all underlying stocks for an index

trade at least once every *n* intervals. Stoll and Whaley (1990) constructed index returns using

the VAR approach to purge the infrequent trade effects. They employed the return innovations

generated from an ARMA model to construct a VAR representation of the data comprising

lagged spot index returns and futures returns. Their results indicate that S&P 500 and MM

index futures returns led their associated stock index returns by approximately 5 minutes;

however, this lead-lag relation is detected only infrequently when the infrequent trade effects

have been purged for a span of 10 minutes or more. These index futures were found to lead

even frequent and active stocks.

The VAR approach remains partially relevant. If the spot, index futures, and index tracking

ETFs prices for a given asset deviate from one another, market forces would work bring them

back to their earlier values to adhere to their long-run relationship expressed by the cost of

carry formula. The singular reliance on the VAR approach fails to address the implied

cointegrating relation between the three index derivative markets as suggested by the

theoretical cost-of-carry relation.

2.2.2 Error Correction Models (ECM's) Approach to Fit Theoretical Cost-of-Carry Relation

The Granger representation theorem states that if a dynamic model (error correction model)

containing a stationary error term and data with one unit root exists, then the variables must be

cointegrated. Consequently, the second branch of literature focuses on the existence of valid

error correction models (ECM's) characterizing the data on spot index, index futures (see, for

example, Shyy et al., 1996; Dwyer et al., 1996; Booth et al., 1999; Tse, 2001; Bose, 2007; Schlusche, 2009), and ETFs.

There are, however, several limitations associated with the empirical application of ECM. In the standard approach applied for the estimation of the error correction model, the adjustment of prices is based on the deviation from the long-rum equilibrium relation, and the speed of adjustment is independent of the size of the deviation. However, in practice, often, the speed of adjustment is accelerated by arbitrageurs if the deviation is sufficiently large to cover the transaction costs. One method to address this problem is to apply the threshold error correction model (TECM) (see, for example, Yadav et al., 1994; Martens, 1998; Theissen, 2012). TECM incorporates a non-continuous movement function that allows the allocation of different coefficients for price adjustments, thus allowing the adjustment speed to vary. If the transaction costs are equal for all investors, usually, two adjustment coefficients, one with respect to the non-arbitrage regime and the other to capture the arbitrage activity, are allowed. However, if the transaction costs vary among different investors, a less restrictive model can be applied, for

example, the smooth transition error correction model (STECM), which was adopted in Tse

(2001), Fung and Yu (2007), and Chen et al. (2013).

However, the threshold error correction model (TECM) requires the transition function to be

exogenously specified, and commonly, there are no theoretical foundation to guide these

specifications, which could contribute to a systematic problem. Furthermore, models that

afford greater flexibility in non-parametric settings also exist, for example, the partially linear

error correction model, which incorporates a density-weighted OLS approach to estimate the

short-run dynamics. In this, the Nadaraya-Watson estimator is employed to estimate the non-

parametric model (see, Gaul, 2005; Gaul and Theissen, 2015). Vortelinos (2014) also

conducted analysis based on non-parametric functions for equity arbitrages.

Considering a more practical approach, Fleming et al. (1996) and Pizzi et al. (1998)

incorporated the residuals generated from the ARMA model into the final estimation of the

ECM. However, this approach could be misleading when the ARMA residuals are combined

with the error correction term. Shyy et al. (1996) employed quote mid-points rather than

transaction prices in the estimation of the ECM (as the former does not tend to suffer infrequent

trade). Care should be taken in obtaining the quote mid-points for index, as only data pertaining

to the best bid prices and best ask prices is required.

2.2.3 Information Share and Common Factor Decomposition Methods

The Hasbrouck (1995) information share and Gonzalo and Granger (1995) common factor

decomposition methods have been widely employed in the literature to examine price

discovery of the same asset traded in different markets. These are composed on a vector error

correction model (VECM), with the aid of a decomposition process included in their

procedures. The Hasbrouck (1995) information share approach decomposes the innovation

terms in VECM and tracks price changes via the permanent component of the innovation. It

compares the speed of adjustments of the innovation terms and generates the contributions of

return or price series to the price discovery process. The Gonzalo and Granger (1995) common

factor decomposition method concentrated on the component in the price change that is

permanently impounded into security prices and serves the function of reflecting new

information or updating information.

Chou and Chung (2006) employed the Hasbrouck information share to analyze the Dow Jones, S&P 500, and NASDAQ indices and their related derivatives. They discovered that after ETFs were quoted using the decimal method (which effectively decreased the minimum tick size of ETFs), the index future led the market. Frommherz (2017) examined the German index market DAX with the Hasbrouck (1995) information share approach. He suggested that the ETFs and futures were in counter-competitive positions; in particular, when the information share for the index futures decreased, the information share for the ETFs increased. The results also indicated that the futures market led the price discovery process and is followed in this regard by the ETFs. So and Tse (2004) employed both the Gonzalo and Granger common factor model and the Hasbrouck information share to analyze the minute-by-minute price data from Hang Seng index, its index futures, and related tracker funds. They discovered that these three markets are interrelated, with the futures market containing the maximum amount of information, followed by the spot market. The tracker fund does not contribute to the process of price discovery. Ates and Wang (2005) examined price discovery between floor traded index futures and electronic traded E-mini index futures for the S&P 500 and NASDAQ-100 index futures markets. They applied both the Gonzalo and Granger common factor model and the

Hasbrouck information share approach and discovered that both E-mini index futures and regular index futures contribute to the price discovery process.

3 Data

In this study, we accessed Thomson Reuters Tick History™ and collected intraday real-time last index values (for futures) and last transaction prices (for ETFs) at a 5-minute frequency over a four-year period, extending from January 2010 to December 2013.[11] We concentrated on the three major European stock markets in the United Kingdom, France, and Germany, where the representative market indices FTSE 100, CAC 40, and DAX 30 were considered. We further classified them into three groups: 1) FTSE group, including the spot index, index futures, and iShare ETFs; 2) CAC group containing the spot index, index futures, and Lyxor ETFs; 3) DAX group of the spot index, index futures, and iShare ETFs.[12] The continuous trading hours for the London Stock Exchange begin from 8:00 to 16:30 in London time, and the same time is followed by CAC trading and DAX. Any data falling into non-overlapping intraday trading times were deleted. Given the fact that the futures contracts for the CAC 40

and DAX are traded between 8:00 and 22:00 Central European Time, the reduced sample for

the futures contracts may introduce bias into the results.

The missing data are spread across the sample period, and this could be due to the technical

problems faced in recording the raw data. The raw data also includes some extreme outliers.

Verousis and Gwilym (2010) suggest deleting the outliner, defined as excessive price changes

above a 5% threshold. We followed this approach and backfilled the unwanted outliers or

missing data using the nearest available index value or transaction price. Since only a handful

of data points were replaced, such "data cleaning" would not have a significant impact on the

quality of the data.

As observed in Section 1.1, concerns with regard to infrequent trade in the constituents prevail.

In particular, many component stocks (such as those present on the S&P500 index) are not

traded sufficiently frequently (Chan, 1992). In this regard, the index markets we considered in

our analysis, FTSE 100, CAC 40, and DAX 30, contained a limited number of constituents,

compared to the 500 constituents in S&P 500. Thus, there is a possibility that not all component

stocks trade in a given time interval were small. Moreover, we examined price discovery across

multimarket and multichannel trades using data with 5-minute time span; consequently, the

infrequent trade problem may not be a significant issue.

3.1 Demeaned Process on Price Series

The relationship between index futures and their underlying spot index is often described as

the cost-of-carry model, $F_{t,T} = S_t e^{(r_{t,T} - K_{t,T})(T-t)}$, where $F_{t,T}$ indicates the futures price at time

t, T represents the contract expiration date, S_t is the spot index value at time t, $r_{t,T}$ is the risk-

free rate within the time period (t, t+1, t+2, …, T), and $K_{t,T}$ is the expected dividend yield for

the underlying investment. The cointegrating relation of spot index and index futures implied

by the theoretical cost-of-carry model is time-varying and could typically vary within one

trading day. Many empirical studies do not address this issue, with a limited number of studies

suggesting strategies to deal this problem. Dwyer et al. (1996), for example, subtracted the

daily average from the logarithmic form of the prices of futures and cash indexes. By doing

this, they managed to eliminate any constant component generated by dividends and interest

rates for the day. Other studies applied the discounted future prices approach and employed a

pre-specified cointegration vector to address this issue (see, for example, Martens, 1998; Tse, 2001; Schlusche, 2009). However, as emphasized by Theissen (2012), since future prices often deviate from values implied by theoretical cost-of-carry models, discounting the future price with regard to certain benchmark risk-free rate would introduce bias in the estimation. Conversely, the demeaning method could eliminate any deviation in futures prices from the values of the cost-of-carry relation, a change that would render the method superior by itself.

Our clean data sample comprised 9 demeaned price series. They were calculated by subtracting the daily average from the intraday log price series (see Table 3 for the descriptive statistics for the demeaned log series).

3.2 Why a Sample Ending in 2013, due to Data Restrictions, is Relevant for 2018?

Our dataset only comprises the last trading day of 2013 and it would be advantageous if we could extend it to the most recent period. However, we are constrained by data availability from the data vendor. To address this problem, we obtained some statistics representing the overall ETFs growth in Europe. This will allow us to explain why the price data of the ETFs

currently used in our paper, grouped under FTSE 100, CAC 40, DAX 30, ending in 2013, is

capable of generalizing comparable results in the near future, especially for the year 2018. The

data are obtained from ETFGI, a leading independent research and consultancy firm on trends

in the global ETF/ETP ecosystem. A detailed description of the ETFs growth is provided in

Table 1.

Table 1 European ETFs Growth 2008–2018

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	July 2018
Asset Value (US$ Bn)	219	226	281	268	331	395	438	488	542	762	788
Growth rate (%)	65.91	3.20	24.34	-4.63	23.51	19.34	10.89	11.42	11.07	40.59	3.41
No. of ETFs	640	833	1069	1227	1325	1375	1459	1542	1560	1610	1675

Source: ETFGI data sourced from ETF/ETP sponsors, exchanges, regulatory filings, Thomson Reuters/Lipper,

Bloomberg, publicly available sources, and data generated in-house.

We purposely classified the above data into three particular time periods: the 2008 financial

crisis, 2010–2013 post-crisis (i.e. our actual sample period in the paper), and 2014–2018 post-

crisis periods. Overall, we found compelling evidence that the two *post-crisis* periods exhibit

similar trends, both in terms of the ETFs asset value and size. Such a high similarity, following

Deloitte Consulting, is owing to the post-crisis quantitative easing bull run in the financial

market (p. 1, https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-

services/performancemagazine/articles/lu_growth-etf-in-europe-012017.pdf). In this regard,

we are confident that it will be appropriate for us to extrapolate our existing research results,

based on January 2010–December 2013, to the future period of 2014–2018. We illustrate these

points in conjunction with the statistics outlined in Table 1 as follows.

The European ETF industry continues to build on the significant growth over the last 10 years

or so. ETF promoters are developing new products by expanding the nature of the ETFs in the

market. ETFGI reported that the assets invested in ETFs listed in Europe increased by 2.13%

during July 2018 to reach US$788 billion at the end of the month. Year-to-date, assets have

increased by 3.17% from $762 billion at the end of 2017. The growth rate of the asset value

undoubtedly varies from time to time. However, it is intriguing to note that, on average, the

asset value of ETFs has grown at almost an identical rate across the two post-crisis periods. In

particular, during the 2010–2013 post-crisis period, the average growth rate of the asset value

was 15.64%, whereas in the 2014–2018 post-crisis period, the estimated average growth rate

was 15.47%. Such a similarity is indeed attributable to the Net Asset Value of the underlying

stock of the ETFs. In particular, the price of ETFs mainly depends on the creation and

redemption mechanism to keep the value of the ETFs in line with the Net Asset Value (NAV)

of the underlying stocks at the end of the trading day on which the transaction was initiated.

Thus, in the two post-crisis periods, no particular structural changes existed in the NAV of the

stock, meaning that the asset values of the ETFs share a similar trend across the two periods

(see Table 1). In fact, NAV trading is also much more common in Europe than in the US, where

the market is significantly more liquid (https://www.ft.com/content/ef4b5106-58aa-11e1-

b9c6-00144feabdc0: Nomura and Tradition launch new ETF trading platform).

Another salient feature of the statistics outlined in Table 1 is that there is comparable evidence

pertaining to the size of the European ETFs in the two post-crisis periods that we consider. The

average size of the ETFs during the post-crisis period 2010–2013 was 1249, whereas the size

of the ETFs during 2014–2018 was 1569. Here, we would like to emphasize that the two

average sizes (per year) are quite comparable, which is particularly true when we look at the

size of the ETFs in the 2008 crisis period alone, which was 640.

To further explain why a sample ending in 2013 is indeed relevant for 2018, we turned the

statistics in Table 1 into a time series graph (see Figure 1). The breakdown of the three time

periods enables us to conclude that the European ETFs saw a steady growing pattern both in the 2010–2013 and 2014–2018 post-crisis periods (Figure 1). ETFs attract long-term position hedgers and liquidity traders rather than arbitragers, as ETFs are traded at a slower frequency than futures and arbitrageurs who care about short-term profitability prefer stocks and futures rather than the ETFs (Deville et al., 2014). Even if there is additional liquidity coming from ETFs due to short-term trading, it will disappear when the market is depressed, leaving mainly hedgers and liquidity traders who focus on long-term positions. Thus, in the longer term, the transaction prices of the ETFs would be expected to exhibit a stable pattern due to the nature of ETFs traders. In addition, with the introduction of MiFID (The Markets in Financial Instruments Directive), which came into force on the 1st of November in 2007 (aiming to promote a harmonized European financial market through a pan-Europe regulatory framework), the diversity of taxation and regulatory requirements, different clearing and settlement systems, and the existence of diverse jurisdictions have been gradually removed and unified. Consequently, we would expect that the value and size of European ETFs to have a steady growing pattern, both in the 2010–2013 and 2014–2018 post-crisis periods.
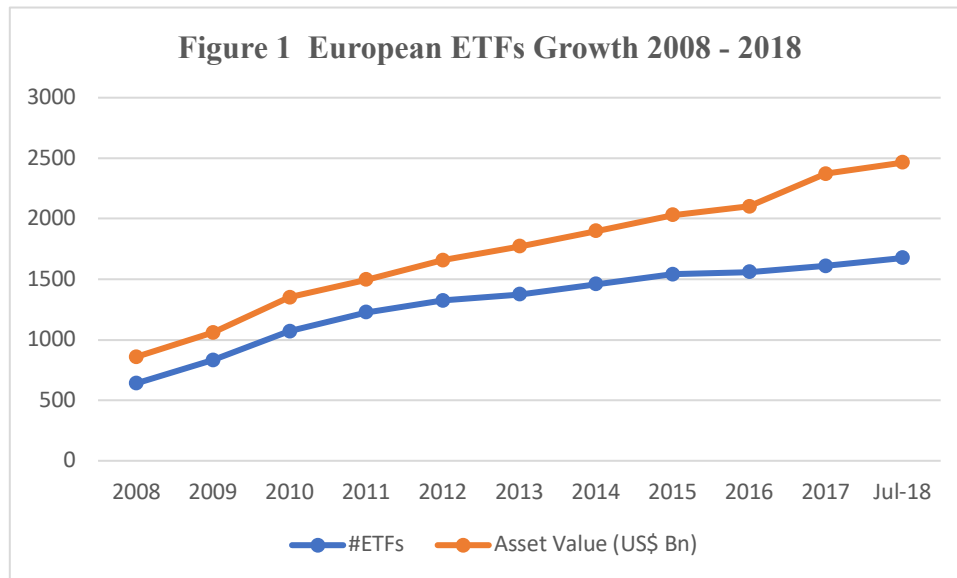
Figure 1 European ETFs Growth 2008 - 2018

Source: ETFGI data sourced from ETF/ETP sponsors, exchanges, regulatory filings, Thomson Reuters/Lipper, Bloomberg, publicly available sources, and data generated in-house.

Finally, it is certainly true that price discovery will be greatly affected, given the incredible changes in the speed of execution of ETFs in the financial markets. In Europe, on the other hand, especially from 2016, the speed of trading in ETFs has not grown much due to the emergence of synthetic ETFs, such as Smart beta ETFs (p. 6, https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-services/performancemagazine/articles/lu_growth-etf-in-europe-012017.pdf). This implies that the trading speed does not seem to be the real driver altering/affecting price discovery to a great extent in recent years. It has been reported that Smart beta ETFs make up most of the new product launches in Europe. They undoubtedly attracted strong inflows from investors seeking

return at a lower cost than actively managed funds due to their synthetic (i.e. highly leveraged) nature. Further, such inflows are particularly strong in Europe. The consequence is that ETFs promoters find it difficult to create and test these new products for investors looking to Smart beta ETFs, as some of them provide less transparency than the traditional ETFs that hold physical securities, resulting in the overall trading speed not growing as much as it should.

3.2.1 Some Further Investigation on the Post-2013 Publications that use ETFs Data

Our current study looks at 5-minute intra-day data over 4 years (January 2010–December 2013) for nine series involving three types of instruments across three markets. We believe that this is quite a substantial and extensive dataset. It is more important to note, however, that although all recent literature used ETFs, there is no existing literature on this topic that has been able to use intra-day data beyond the year 2011 (see Table 2). We suspect that the data problem may be common. Further, these studies only cover post-2013 literature that involve ETFs, including the most recent ones by Frommherz (2017) and Deville et al. (2014), which only cover few years/months of data between 2007–2011. Since there is no literature on this topic that has demonstrated the use of intra-day data beyond the year 2011, we suspect that the data problem

may be common. Our current study looks at 5-minute intra-day data over 4 years (January 2010–December 2013), which is a more substantial dataset. We also collected data of 9 instruments in order to obtain complete coverage of different segments (trading venues) of the European market. Although it would undoubtedly be better to bring the dataset up to the present time, we believe that we have achieved the best dataset available for such a study. Therefore, we are confident in the robustness of our main finding that ETFs have gradually taken over the price discovery role from futures.

Table 2 Some Further Investigation on the Post-2013 Publications that use ETFs Data

Post-2013 ETFs-related Publications	Price Series	Data Frequency	Time Period
Ivanov (2013)	Commodities spot, ETFs and futures prices	*1 minute*	March–August 2009
Ivanov et al. (2013)	Spot, ETFs and futures of the DJIA, S&P500, S&P400, NASDAQ 100 and Russell 2000	*1 minute*	January 2001–March *2011*
Krause et al. (2014)	ETFs and component stock return and price data, for nine Select Sector SPDR ETFs	Daily	March 2003–December 2013
Deville et al. (2014)	Spot, ETFs and futures of the CAC 40	*Intraday*	Two periods surrounding January *2011*
Madhavan and Sobczyk (2016)	All US domiciled ETFs	Daily	January 2014
Frommherz (2017)	German equity index DAX, DAX futures, as well as DAX options and the top-level order book of the iShares DAX ETFs	*1 second*	July 2007–December *2009*

4 Methodology

The purpose of this study was to attempt to gain an understanding regarding the relative efficiency in the price discovery process of three index derivative markets. As observed in Sections 2.2.1 and 2.2.2, the spot index, index futures, and index tracking ETFs are based on the same underlying assets; thus, these markets are affected by the same information set. If the spot, futures, and ETFs prices for a given asset deviate from each another, the market forces would function to realign them to the same values to follow their long-run relationship given by the cost-of carry-formula. The examination of the deviations of the three index derivative markets from the long-run equilibrium relation helps us understand the way in which these markets adjust their prices in relation to common information received. Then, we can analyze these markets' ability to transmit information and reveal their relative efficiency in the price discovery process. The Hasbrouck (1995) information share and the Gonzalo and Granger (1995) common factor weights were applied in our study to investigate the contribution of each market to the price discovery process. These two methods essentially analyze the common factor among cointegrated price series to examine the way in which the information is transmitted across the markets.

4.1 Hasbrouck (1995) Information Share Method

The Hasbrouck (1995) information share method is based on the existence of q co-integrated I(1) price series defined by the q-dimensional price vector $P_t = (p_{1t}, p_{2t}, ..., p_{qt})$. In our paper $q = 3$ corresponds to the three groups of data based on the underlying equity indices, namely FTSE 100, CAC 40 and DAX 30. In particular, when $q = 3$, $P_t = (FTSE\_SPOT, FTSE\_FT, FTSE\_ETF)$, when $q = 3$, $P_t = (CAC\_SPOT, CAC\_FT, CAC\_ETF)$, and when $q = 3$, $P_t = (DAX\_SPOT, DAX\_FT, DAX\_ETF)$. Hence, overall, we run three separate estimations in analyzing these different sets of variables.

Our testable framework begins with Johansen and Juselius (1990) cointegration test in examining the co-integrating relationship among the price variables. The test sets out to estimate the following VECM:

$$\Delta P_t = \Pi P_{t-1} + \sum_{j=1}^{k} A_j \Delta P_{t-j} + e_t \qquad (1)$$

where $\Pi = \alpha \cdot \beta'$, A_j is a q x q matrix of coefficients, α is the error correction vector, β is the co-integrating vector and e_t is a zero-mean vector of innovations with a covariance matrix Ω. The term ΠP_{t-1} captures the long-run equilibrium of the variables in the system, whereas the term $\sum_{j=1}^{k} A_j \Delta P_{t-j}$ incorporates the short-run dynamics of the system.

The coefficient matrix Π contains information about the co-integrating relationship between the variables P_t. In particular, Johansen and Juselius (1990) shows that the rank of the matrix Π defines the number of co-integrating relationships in the system, which may be determined using the Johansen and Juselius (1990) Trace Test to test for the null hypothesis of at most r co-integrating relationships and at least $h=q-r$ common factors. The test statistic is given by:

$$\lambda_{TRACE} = -T \sum_{j=r+1}^{p} \ln\left(1 - \hat{\lambda}_j\right) \qquad (2)$$

where T is the sample size and $\hat{\lambda}_1 > \hat{\lambda}_2 > ... > \hat{\lambda}_q$ are the eigenvalues of squared canonical correlation between the two residual vectors from the level and first-difference regressions, respectively.

The Hasbrouck (1995) information share method is based on the information embedded in the matrix Π of equation (1). In particular, it involves a process of decomposing the impact of innovations (news) and allocate such an impact to individual price series. Hasbrouck (1995) decomposes the variance of the common factor innovations and defines the information share of a market as the proportion of the variance of the common factor innovations that is attributable to innovations in that market. The decomposition begins with a vector moving average (VMA) representation of Eq. (1) that is:

$$\Delta P_t = \Psi(L)e_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + ... \qquad (3)$$

An integrated form of Eq. (3) is then:

$$P_t = \Psi(1)\sum_{s=1}^{t} e_s + \Psi^*(L)e_t \qquad (4)$$

The matrix $\Psi(1)$ in Eq. (4) is the sum of the moving average coefficients, where

$\Psi(1) = I + \theta_1 + \theta_2 + ...$, which implies $\beta'\Psi(1) = 0$. Since $\Psi(1)e_t$ represents the long-run

impact of the innovations on q price series, the estimation of $\Psi(1)$ is crucial in computing the

information share. Denoting $\psi = (\psi_1, \psi_2, ..., \psi_q)$ as a common row vector in $\Psi(1)$ and τ as a

column unit vector, Eq. (4) may be re-written as:

$$P_t = \tau\psi\sum_{s=1}^{t} e_s + \Psi^*(L)e_t \qquad (5)$$

Eq. (5) above reveals that the price of an index is composed of two parts, the first part is the

common factor component $\tau\psi\sum_{s=1}^{t} e_s$, and the second part is the transitory portion $\Psi^*(L)e_t$.

The increment ψe_t can be interpreted as the component of the price change which is

permanently impounded into security prices and responsible for reflecting new information.

The variance of ψe_t, which is $\text{var}(\psi e_t) = \psi\Omega\psi'$, is then used to compute the information share.

Hasbrouck (1995) shows that the information share (IS) for a market j is given by:

$$\frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi'} \tag{6}$$

In general, the price innovations may be contemporaneously correlated. In order to address such an issue, Hasbrouck (1995) performed the Cholesky factorization on the covariance matrix Ω, such that $\Omega = FF'$. Thus, Eq. (6) may be re-written as:

$$\frac{\left([\psi F]_j\right)^2}{\psi \Omega \psi'} \tag{7}$$

where F is a lower triangular matrix with elements $F = \left(f_{ij}\right)_{i,j=1,\dots,q}$.

Baillie and Bollerslev (2002) show that the values of ψ are directly related to γ that defines the vector Γ, such that Eq. (6) and Eq. (7) may be formulated in the forms of Eq. (8) and Eq. (9), respectively:

$$\frac{\gamma_j^2 \Omega_{jj}}{\gamma \Omega \gamma'} \tag{8}$$

$$\frac{\left([\gamma F]_j\right)^2}{\gamma \Omega \gamma'} \tag{9}$$

Due to the orthogonalization of the covariance matrix Ω, a unique measure of IS for each

market may not be obtained straightforwardly. Instead, an upper and a lower bound are defined

with the largest (smallest) IS value being obtained when the variable is first (last) in the

Cholesky ordering. Here, the upper and lower bounds of a market's IS with the price series

being the first and last series are given by IS_1 (Eq. 10) and IS_q (Eq. 11), respectively:

$$IS_1 = \frac{\left[\sum_{i=1}^{q} \gamma_i f_{i1}\right]^2}{\left[\sum_{i=1}^{q} \gamma_i f_{i1}\right]^2 + \left[\sum_{i=2}^{q} \gamma_i f_{i2}\right]^2 + ... + \left[\gamma_q f_{qq}\right]^2} \qquad (10)$$

$$IS_q = \frac{\left[\gamma_q m_{qq}\right]^2}{\left[\sum_{i=1}^{q} \gamma_i f_{i1}\right]^2 + \left[\sum_{i=2}^{q} \gamma_i f_{i2}\right]^2 + ... + \left[\gamma_q f_{qq}\right]^2} \qquad (11)$$

Baillie and Bollerslev (2002) suggest that the midpoint of these two bounds may be used as a

measure of price discovery for each market.

4.2 The Gonzalo and Granger (1995) Common Factor Weights Model

While Hasbrouck's (1995) information share method uses the variance of the common factor

innovations to measure price discovery, such that the contribution by each market to the

variance is the information share, Gonzalo and Granger's (1995) common factor weights

method concentrates on an error correction process which impounds permanent shocks to raise

system disequilibrium, with the error correction coefficient as the contribution of each market

to the common factor. Central to Gonzalo and Granger (1995) is a permanent-transitory

decomposition process from which price discovery may be measured. Such a decomposition

process closely follows the Stock and Watson (1988) common trend representation of P_t, which

is:

$$P_t = \Gamma_1 f_t + G_t \tag{12}$$

where P_t is a vector of I(1) time series of prices (for example, actual transaction prices;

bid/offer quotes); Γ_1 is the loading matrix, f_t is the common factor, and G_t is the transitory

component that has no permanent effect on P_t. Gonzalo and Granger (1995) further impose a

linear restriction on P_t in order to identify f_t, that is:

$$f_t = \phi_j P_t \tag{13}$$

where ϕ_j is the coefficient vector which associates the prices with the common factor. Harris

et al. (2002a) and Baillie et al. (2002) suggested that ϕ_j can be normalized such that they pick

up the weights of market j's contributions to the common factor. The higher the common factor

weight ϕ_j, the greater is the importance of market j's contributions to the long-term stochastic

trend.[13]

Gonzalo and Granger (1995) proved that ϕ_j is orthogonal to the error correction coefficient

vector α in the vector error correction representation of P_t, such that $\alpha_\perp = \phi'$. Additionally,

$\alpha_\perp$ can be found by estimating this vector error correction representation of P_t via OLS, which

is:

$$\Delta P_t = \alpha \beta' P_{t\text{-}1} + \sum_{j=1}^{k} A_j \Delta P_{t\text{-}j} + e_t \qquad (14)$$

where α represents an error correction vector; β is the co-integrating vector; e_t represents a

vector of serially uncorrelated innovations with zero-mean. The fundamental assumption is that

when one security is traded in several markets, the prices of the security in different markets

will not drift too much from each other, and the price differentials are captured by the error

correction term.

Following Johansen (1988), the maximum likelihood estimator of $\alpha_\perp$ can be found by solving

Eq. (15):

$$|\lambda S_{00}\text{-}S_{01}S_{11}^{-1}S_{10}| = 0 \quad [14] \qquad (15)$$

for the eigenvalues $\widehat{\lambda_1} > \cdots > \widehat{\lambda_n}$ and eigenvectors $\widehat{M} = (\widehat{m_1}, \dots, \widehat{m_n})$. Normalising the

eigenvectors such that $\widehat{M}'S_{00}\widehat{M} = I$, the selection of $\hat{\alpha}_\perp$ is given by Eq. (16):

$$\hat{\alpha}_\perp = (\widehat{m}_{r+1}, \dots, \widehat{m}_n) \tag{16}$$

It is important to note that the selection of $\hat{\alpha}_\perp$ is according to the last column of the eigenvector

$\widehat{M}$, and $\alpha_\perp = \phi'$.

Following the Gonzalo and Granger (1995) common factor weights model, our testable

framework is explained as follows. We allow the long-run common stochastic factor shared by

security prices on different markets to be expressed as a linear combination of these series

where:

$$f_t = \emptyset_1 PS + \emptyset_2 PF + \emptyset_3 PE \tag{17}$$

and f_t is the common factor, and PS, PF, and PE are the price series with respect to spot index,

index futures and ETFs. ϕ_j can be seen as the contributions from each index derivative market

to the common factor f_t.

5 Empirical Results

5.1 Preliminary Data Analysis

Our empirical analyses involved the application of Hasbrouck's (1995) information share and

Gonzalo and Granger's (1995) common factor weights approaches. Since these methods are

constructed on a VECM, which requires non-stationarity, or equivalently, a single unit root $I(1)$

of the price series. In order to determine the data's non-stationarity condition, we performed

the Augmented Dickey-Fuller (ADF) unit root tests on all demeaned log price series under each

of the three markets (see Table 3). The unit root tests were conducted on levels and

subsequently on the first differences in the respective series. The null hypothesis that the series

contains a unit root cannot be rejected at 5% significance level, suggesting the existence of at

least one unit root in the demanded series. Since the first differences corresponding to all price

series were stationary, it follows that all demeaned price series are $I(1)$ variables.

Table 3 Descriptive Statistics and ADF Results of Nine Demeaned Price Series

Table 3 examines nine demeaned price series in logarithms during 2010 to 2013, and the data covers the period from January 2010 to December 2013. Our data sample contains intra-day five-minute transaction prices of the spot index, index futures, and ETFs grouped under three major European market indices FTSE 100, CAC 40, and DAX 30. The demeaned series are calculated through the subtraction of the daily average from the log series.

FTSE 100 Demeaned Log Prices

	FTSE 100 Spot Index				FTSE 100 Index Futures				iShare FTSE 100 ETF			
	2010	2011	2012	2013	2010	2011	2012	2013	2010	2011	2012	2013
ADF Log Price	−2.217499 (> 0.10)	−2.352961 (> 0.10)	−3.399739 (> 0.10)	−1.299864 (> 0.10)	−2.336921 (> 0.10)	−2.397318 (> 0.10)	−2.215798 (> 0.10)	−1.278252 (> 0.10)	−2.279457 (> 0.10)	−2.303084 (> 0.10)	−2.316053 (> 0.10)	−1.343524 (> 0.10)
ADF 1st Difference	−115.1299 (< 0.0001)	−161.2480 (< 0.0001)	−161.6907 (< 0.0001)	−160.0915 (< 0.0001)	−163.4885 (< 0.0001)	−164.8831 (< 0.0001)	−165.2602 (< 0.0001)	−162.9772 (< 0.0001)	−129.4342 (< 0.0001)	−103.7695 (< 0.0001)	−121.5548 (< 0.0001)	−177.0365 (< 0.0001)
Mean	−0.028642	0.008925	0.021266	0.139425	−0.029801	0.007729	0.019548	0.137915	−0.028839	0.007080	0.019959	0.136282
Variance	0.049300	0.056769	0.029572	0.028316	0.049619	0.055716	0.030129	0.029608	0.047904	0.056887	0.028612	0.028867
Skewness	−0.216936	−0.592822	−0.972159	−0.388473	−0.228756	−0.606306	−0.838144	−0.400989	−0.216052	−0.548843	−1.026831	−0.370460
Kurtosis	2.219396	2.088862	3.485713	2.600396	2.231447	2.139559	3.132329	2.595813	2.227154	2.003962	3.578135	2.637226

CAC 40 Demeaned Log Prices

	CAC 40 Spot Index				CAC 40 Index Futures				iShare CAC 40 ETF			
	2010	2011	2012	2013	2010	2011	2012	2013	2010	2011	2012	2013
ADF Log Price	−2.909740 (> 0.01)	−1.079436 (> 0.10)	−2.115898 (> 0.10)	−2.142514 (> 0.10)	−3.166403 (> 0.01)	−1.118723 (> 0.10)	−2.036411 (> 0.10)	−2.126980 (> 0.10)	−3.521735* (> 0.01)	−1.003647 (> 0.10)	−2.543171 (> 0.10)	−2.291995 (> 0.10)
ADF 1st Difference	−116.6494 (< 0.0001)	−73.49569 (< 0.0001)	−73.54314 (< 0.0001)	−72.28754 (< 0.0001)	−164.3948 (< 0.0001)	−73.08876 (< 0.0001)	−165.2602 (< 0.0001)	−72.26399 (< 0.0001)	−162.1051 (< 0.0001)	−74.49029 (< 0.0001)	−73.95681 (< 0.0001)	−73.43109 (< 0.0001)
Mean	−0.046611	−0.097420	−0.159990	0.005556	−0.047535	−0.097758	−0.160291	0.005600	−0.042205	−0.100797	−0.165310	−0.002359
Variance	0.046997	0.126947	0.054233	0.053597	0.047051	0.125997	0.055441	0.053789	0.038428	0.131949	0.047437	0.051983
Skewness	−0.370360	−0.377781	−0.452395	0.111020	−0.390621	−0.376269	−0.462285	0.119634	−0.259819	−0.366647	−0.257676	−0.020454
Kurtosis	2.509653	1.440377	2.251355	1.694933	2.574789	1.436259	2.221614	1.681538	2.724299	1.398148	2.141125	1.750645

Table 3 Descriptive Statistics and ADF Results of Nine Demeaned Price Series (Continued)

DAX 30 Demeaned Log Prices

	DAX 30 Spot Index				DAX 30 Index Futures				iShare DAX 30 ETF			
	2010	2011	2012	2013	2010	2011	2012	2013	2010	2011	2012	2013
ADF Log Price	−1.683566 (> 0.10)	−1.405687 (> 0.10)	−2.306721 (> 0.10)	−1.299864 (> 0.10)	−1.655498 (> 0.10)	−1.356741 (> 0.10)	−2.215798 (> 0.10)	−1.278252 (> 0.10)	−1.661114 (> 0.10)	−1.336331 (> 0.10)	−2.316053 (> 0.10)	−1.343524 (> 0.10)
ADF 1st Difference	−117.6191 (< 0.0001)	−165.0181 (< 0.0001)	−163.6951 (< 0.0001)	−161.9509 (< 0.0001)	−165.5775 (< 0.0001)	−166.1769 (< 0.0001)	−167.4666 (< 0.0001)	−162.4208 (< 0.0001)	−118.1974 (< 0.0001)	−119.9210 (< 0.0001)	−167.0474 (< 0.0001)	−162.1924 (< 0.0001)
Mean	−0.058285	−0.001176	0.041169	0.232599	−0.059552	−0.001866	0.039701	0.231128	−0.058749	−0.009846	0.021204	0.202050
Variance	0.061394	0.115620	0.063575	0.061413	0.061722	0.115826	0.063528	0.061413	0.059527	0.117571	0.062321	0.058345
Skewness	0.460441	−0.505788	−0.221172	0.411917	0.449778	−0.500076	−0.223112	0.409776	0.494365	−0.507634	−0.310070	0.496534
Kurtosis	2.767574	1.706595	2.073963	2.176698	2.761418	1.696088	2.221614	2.180896	2.776062	1.684973	2.108852	2.261643

Notes: 1) We examine nine demeaned price series in logarithms, from 2010 to 2013. Our data sample contains intra-day five-minute transaction prices of the spot index, index futures, and ETFs grouped under three major European market indices FTSE 100, CAC 40, and DAX 30. The data covers the period from January 2010 to December 2013. 2) The demeaned series are calculated through the subtraction of the daily average from the log series. 3. Our empirical analyses involve the use of the permanent transitory decomposition method by Gonzalo and Granger (1995). The method is constructed on a vector error correction model (VECM), which requires non-stationarity of the price series. Thus, we performed the Augmented Dickey-Fuller (ADF) unit root tests on all nine price series of equity indices, grouped under the three major European market indices. The ADF unit root tests were carried out on levels and then on first differences of these time series. The results confirm that all series are integrated of order 1 across all classified markets.

5.2 Information Share Results

Our estimations of the Hasbrouck (1995) information share have been summarized in Table 4.

Upper/lower bounds were achieved by supplying a price variable in the first/last equation of

VECM. Following Harris et al. (2002a) and Baillie et al.'s (2002) methods, the mean of the

upper and lower bounds has also been reported. The estimated upper and lower bounds show

a great deviation from each other in most cases, rendering the identification of the information

share rather difficult.[15] As observed by Hasbrouck (2003) and Baillie and Bollerslev (2002),

wide upper and lower bounds were caused due to high values of correlation between

innovations, because the calculation of the upper bound (defined as the largest IS value) must

include the correlation between innovations.

Table 4 Information Share and Common Factor Weights Results

Table 4 first reports the calculations of Hasbrouck (1995) information share with error bounds. Subsequently, it presents the estimated Gonzalo-Granger common factor weights of the 9 time-series grouped under FTSE, CAC, and DAX respectively, summarized in the column denoted by G-G. The selected lag length for the tested VECM was determined by the Akaike Information Criterion.

FTSE 100

	FTSE 100 Spot Index				FTSE 100 Index Futures				iShare FTSE 100 ETFs				
	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Lags
2010	0.53205	0.05486	0.293455	34%	0.91062	0.39736	0.65399	31%	0.21129	0.08797	0.14963	**35%**	14
2011	0.52504	0.01648	0.27076	20%	0.97354	0.45698	0.71526	**68%**	0.23039	0.02535	0.12787	12%	13
2012	0.60228	0.00464	0.30346	37%	0.99333	0.3957	0.694515	22%	0.44166	0.00656	0.22411	**41%**	11
2013	0.77441	0.00265	0.38853	47%	0.93333	0.17659	0.55496	4%	0.77737	0.04466	0.411015	**49%**	13

CAC 40

	CAC 40 Spot Index				CAC 40 Index Futures				Lyxor CAC 40 ETFs				
	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Lags
2010	0.22024	0.08443	0.152335	35%	0.81415	0.68111	0.74763	20%	0.30542	0.18584	0.24563	**45%**	8
2011	**0.11768**	**0.10094**	**0.10931**	26%	**0.8233**	**0.8125**	**0.8179**	39%	**0.17997**	**0.1731**	**0.176535**	35%	13
2012	0.28051	0.00103	0.14077	22%	0.99391	0.7181	0.856005	**48%**	0.14164	0.00576	0.0737	30%	7
2013	0.42931	0.00101	0.21516	20%	0.98281	0.56021	0.77151	**63%**	0.27499	0.01008	0.142535	17%	11

Table 4 Information Share and Common Factor Weights Results (Continued)

DAX 30

	DAX 30 Spot Index				DAX 30 Index Futures				iShare DAX 30 ETFs				
	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Upper	Lower	Mean	G-G	Lags
2010	0.34094	0.00173	0.171335	34%	0.99949	0.65854	0.829015	29%	0.27453	0.00006	0.137295	**37%**	15
2011	0.14539	0.05868	0.102035	33%	0.93716	0.83418	0.88567	32%	0.16279	0.05843	0.11061	**35%**	17
2012	0.2992	0.05695	0.178075	45%	0.9316	0.61482	0.77321	9%	0.38305	0.06791	0.22548	**46%**	13
2013	0.55181	0.01802	0.284915	**41%**	0.98124	0.43406	0.70765	18%	0.40757	0.01661	0.21209	**41%**	13

Notes: 1) The estimated upper and lower bounds are widely separated in most cases, implying high correlations among any pair of the three price series under each index market. For the CAC 40 index markets in the year 2011, however, the upper and lower bounds for the information share are close enough to generate meaningful results. CAC 40 index futures take the lead in price discovery, with Lyxor CAC 40 ETFs being the second resort for information in 2011. This has been validated through the estimated common factor contributions of spot, futures, and ETFs in the CAC group in 2011.

2) From the common factor weights analysis, we can observe that 1. in general, ETFs lead price discovery in the FTSE and DAX groups, followed by spot and futures. The futures markets exercised an important role in price leading discovery only in 2011 in the FTSE group, forming an exception. 2. Futures contracts played a significant role in price discovery in CAC group, with one exception, that is, in 2010, Lyxor CAC 40 ETFs led the market ahead of spot and futures.

However, it is also worth noticing that for the CAC 40 index markets in the year 2011, the upper and lower bounds for the information share were close enough to yield consequential results. In this case, the upper and lower bounds were 0.118 and 0.101 for the spot index, 0.823 and 0.813 for the futures, 0.180 and 0.173 for the ETFs respectively. This result indicates that, first, the residual correlations among any pair of the three price variables under the CAC index market for 2011 was probably not high. Second, the index futures took the lead in price discovery, with Lyxor CAC 40 ETFs being the second defining element in the process. The common factor weights analysis results provided additional validation to this result for 2011 (see Section 5.3).

5.3 Common Factor Weights Results

To commence our analysis, we first performed Johansen & Juselius's (1990) trace test for the index derivative markets under FTSE, CAC, and DAX for the period 2010 to 2013 (see Table 5). Evidently, as the prices for the futures contracts, ETFs, and index values for the same index market were based on the same set of underlying assets, these prices should contain one common informational factor, in spite of the diverse informational roles played by these individual instruments. To examine whether the price series of futures, ETFs, and spot index shared a common factor (i.e., was cointegrated), we performed Johansen & Juselius's (1990) trace test with the null hypothesis such that there exists at most *r* cointegrating vectors among them. Based on the results presented in Table 5, the null hypothesis that there are most 1 cointegrating vector was rejected for cases from all sample periods, as the test statistics λ_{trace} were all found to be significantly greater than the 5% critical value. In conjunction with an additional test result of the null of at most 2 cointegrating vectors (in this case, the null was not rejected for cases across all years as λ_{trace} was below the 5% critical value), we concluded that that the three demeaned log price series of spot index, index futures, and index tracking ETFs

were all cointegrated in each of the three index markets FTSE, CAC, and DAX across all sample years. In particular, we learned that the three series are cointegrated with two cointegrating vectors, which implies that they share one common stochastic trend.

Table 5 Johansen and Juselius (1990) Trace Test

Table 5 presents Johansen & Juselius's (1990) trace test result to determine the cointegrating rank of the long-run π matrix. The results suggest that the demeaned log prices of equity indices, futures, and ETFs of

each of the FTSE, CAC, and DAX index markets are all cointegrated over all sample periods.

FTSE 100

	2010		2011		2012		2013	
Hypothesized No. of CV(s)	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%
r = 0	356.4063*	42.91525	425.4435*	42.91525	565.0639*	42.91525	202.6593*	42.91525
r = 1	30.50086*	25.87211	30.00253*	25.87211	68.14124*	25.87211	42.73061*	25.87211
r = 2	10.41709	12.51798	8.882032	12.51798	12.47922	12.51798	12.05022	12.51798

CAC 40

	2010		2011		2012		2013	
Hypothesized No. of CV(s)	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%
r = 0	604.4711*	42.91525	639.9740*	42.91525	663.9006*	42.91525	588.7930*	42.91525
r = 1	26.37691*	25.87211	26.43141*	25.87211	27.80642*	25.87211	28.52341*	25.87211
r = 2	5.370142	12.51798	6.356120	12.51798	4.438433	12.51798	9.717103	12.51798

Table 5 Johansen and Juselius (1990) Trace Test (Continued)

DAX 30

Hypothesized No. of CV(s)	2010		2011		2012		2013	
	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%	λ_{trace}	Critical Value at 5%
r = 0	1015.703*	42.91525	1114.390*	42.91525	981.5404*	42.91525	851.8932*	42.91525
r = 1	46.39684*	25.87211	45.51405*	25.87211	40.12582*	25.87211	30.75531*	25.87211
r = 2	9.615335	12.51798	5.649982	12.51798	3.859387	12.51798	8.338801	12.51798

Notes: 1) Statistical significance at the 95% level or greater is signified by *. 2) We perform the Johansen and Juselius (1990) Trace Test to assess the co-integrating rank of the long-run π matrix. The results suggest that, in each separate market, there exists at least one common stochastic trend among i) spot index, index futures, and iShare ETFs of FTSE, ii) spot index, index futures, and Lyxor ETFs of CAC, and iii) spot index, index futures, and iShare ETFs of DAX.

Table 4 presents a summary of the estimated Gonzalo and Granger (1995) common factor decompositions of the 9 time series for the FTSE, CAC, and DAX groups. For the FTSE data set, the iShare FTSE 100 ETFs was in a dominant position in the price discovery process, as it generated the highest contributions to the common factor in the majority of sample periods in 2010, 2012, and 2013. Conversely, the estimated common factor weights of the spot index market closely replicated those of the ETFs market in these years, while the futures market made the least contribution to the common factor. It is interesting to note that, however, in 2011, the FTSE futures market took the lead, as the estimated contribution of such a market to the overall price discovery process was as high as 68%, followed by the spot, with the ETFs market contributing the least for that year.

For the German market, the iShare DAX 30 ETFs assumed absolute dominance in the price discovery process, as the estimated common factor weights consistently remained the highest throughout the sample periods. It appears that the spot index market was the second largest contributor to the price discovery process, as the common factor weights closely followed those of the index tracking ETFs market. The DAX index futures market did not play a leading informational role in the overall market, because the common factor weights for the futures were the smallest in the three markets.

With regard to these findings, we discovered that over time, ETFs have become the dominant vehicle for price discovery in relation to the two main European stock market indices, one in Britain and the other in Germany. As stated earlier, this offers further contradictory findings to Hasbrouck (2003), Schlusche (2009), and Theissen's (2012) works, while they are similar to the conclusions drawn by Ivanov et al. (2013) and Chou and Chung (2006). However, our study is far more comprehensive than Ivanov et al.'s (2013) and Chou and Chung (2006).

Ivanov et al. (2013) utilized the Hasbrouck (1995) information share and Gonzalo and Granger (1995) common factor weights approach to study indices, index futures, and index ETFs across DJIA, S&P 500, S&P 400, NASDAQ-100, and Russell 2000 in the period stretching from January 2000 to December 2012, but only at the daily level. Chou and Chung (2006) conducted the analysis over a considerably shorter period of intraday data extending from October 2000 to April 2001 and found that ETFs led the price discovery only after ETFs they were quoted using the decimal instead of the fraction method. However, our study covers four years of data from 5-minute intervals that includes three types of instruments across multiple markets, and thus, we were able to confirm the increased role of ETFs in the price discovery process in a more robust manner and contribute to the wider policy debate regarding the role of ETFs in stock markets.

For French markets, the index market Lyxor CAC 40 ETFs played a significant role as a source of information transmission in 2010 and was followed in this regard by the spot and index futures markets. For the majority of the sample periods studied in 2011, 2012, and 2013, however, we discovered compelling evidence that the CAC 40 index futures market headed the price discovery process. This result is compatible with Deville et al.'s (2014), who observed that the Lyxor CAC 40 ETFs are less attractive to arbitrageurs in comparison to the CAC 40 index futures, as Lyxor CAC 40 ETFs were traded at a relatively lesser frequency, and arbitrageurs who look for opportunities offering short-term profitability may prefer futures and stocks over the ETFs. As arbitrage seems to be the driving factor in price leadership in the spot-future markets (Theissen, 2012), this might be reason that the CAC 40 index futures is leading the price discovery over the CAC 40 ETFs.

6 Conclusion

The purpose of this study was to attempt to understand the way in which information is transmitted among index derivative markets and the relative importance of each market's contribution to the price discovery process. We focused on three major index derivative markets of spot index, index futures, and the index tracking ETFs in three major European countries, Britain, France, and Germany. The relevant index markets utilized in our analysis included FTSE 100, CAC 40, and DAX 30; these form the destination markets to which the information is transmitted by the index derivative markets.

Our empirical analysis involved intraday transaction prices data at a 5-minute frequency over a four-year period. The Gonzalo and Granger (1995) common factor weights results suggested that 1) index tracking ETFs lead the price discovery process, followed by spot and futures in the FTSE and DAX groups; 2) index tracking ETFs led price discovery ahead of spot and futures in 2010 only, in the CAC group; 3) index futures contracts played a significant leading role in the price discovery process in CAC group, primarily due to the lower trading frequency of ETFs, according to Deville et al.'s (2014) observation.

In addition to Gonzalo and Granger's (1995) common factor weights method, we computed the Hasbrouck (1995) information share with error bounds. However, the estimated upper and lower bounds were found to be far apart in most cases, with the CAC 40 index markets in 2011 forming the only exception; for this market, the two bounds for the information share were close enough to invalidate meaningful results. We observed that CAC 40 index futures take the lead in price discovery, with Lyxor CAC 40 ETFs forming the second alternative for information in that year.

6.1 Regulatory Implications

1. Although our data suggests compelling evidence for ETFs forming the lead in price information in the FTSE 100 index market, whether sustained (long-term) success can be witnessed in the application of ETFs in this position is a question that remains to be answered. The current scenario is weighed down by many uncertainties due to Brexit, especially with regard to whether or not and when a regulatory framework will be provided that will allow the UK access to the European market. These are challenges in terms of accessibility faced by the UK-based providers. For continuing success in ETFs, therefore, it is crucial for Britain and the European Union to adapt to a changing financial market.

2. Empirical evidence reveals that ETFs attract a greater number of short-term investors rather than long-term ones. Consequently, the additional liquidity perceived to be derived from ETFs due to short-term trading when the market is in a state of boom may be illusory, if the financial market is in depression, as the short-term traders will exit the market. Considered in this respect, ETFs appear to be double-edged swords: they can increase the price volatility of the stocks they own, while exacerbating the volatility of the financial market (due to the behavior of short-term traders).[16] This calls for Financial Conduct Authority (FCA) and Prudential Regulation Authority (PRA) in UK and the Federal Financial Supervisory Authority (BaFin) in Germany to consider curtailing the growth of ETFs or to ensure the trading remains organized. Financial advisers in these countries may work at a fiduciary standard as a result of regulatory reforms, so that they are compelled to invest clients' money as carefully as if it was their own.

3. The boom in the European ETF industry is driven by the post-credit crisis, which has quantitatively eased the bull's run in the financial markets.[17] Regulators must attempt to improve their market oversight following the financial crisis and that would involve rendering

the trading process more transparent. Enhancing the efficiency of ETF trading can offer real benefits to investors. In a low-interest rate environment, once clients understand that they can save one or two basic points through more efficient ETF trading, they will also realize that it is possible to instantaneously enhance the prospective long-term returns on their investments.

Notes

1. https://www.zacks.com/stock/news/71077/japan-etfs-one-year-after-the-fukushima-disaster; https://www.nasdaq.com/article/japan-etfs-one-year-after-the-fukushima-disaster-etf-news-and-commentary-cm126489

2. https://www.ft.com/content/9bca103a-dd9d-11e6-86ac-f253db7791c6

3. http://www.investmenteurope.net/opinion/european-etf-industry-marks-time-high-2017/

4. In fact, the assets owned by the European ETF industry has been increasing for six consecutive years: the average annual growth rate of ETFs in Europe is 20.4% (https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-services/performancemagazine/articles/lu_growth-etf-in-europe-012017.pdf) and such increase in 2017 constituted a new unsurpassed hike (http://www.investmenteurope.net/opinion/european-etf-industry-marks-time-high-2017/).

5. https://www.ft.com/content/9bca103a-dd9d-11e6-86ac-f253db7791c6

6. Most studies pertaining to the price discovery process for the futures and spot markets indicate that the futures take the lead, with only a few studies reporting a weak effect of spot market as the leader in futures markets, such as those of Choi and Subrahmanyam (1994), Fleming et al. (1996), and Chu et al. (1999).

7. See examples at https://www.ici.org/pdf/2017_factbook.pdf.

8. It is also worth noting that the creation or redemption of ETF shares transpires post trading hours and is announced at the end of a trading day, while the buying and selling of stocks and ETF shares takes place during trading hours. Consequently, it could influence the price movement of underlying stocks on the subsequent trading day; this is possibly the reason due to which the price volatility of ETFs got redirected to their underlying stocks and ETFs became the leader of stocks in price discovery (see Krause et al., 2014).

9. Decimalization reduces the trading costs of ETFs.

10. Deville et al. (2014) studied the impact of CAC 40 ETFs on spot and futures pricing and liquidity.

11. Our dataset only comprises the last trading day of 2013 and it would be useful if we can extend it to the most recent period. However, we are constrained by data availability from the data vendor. We notice most recent literature on this topic such as Ivanov (2013) and Ivanov et al. (2013) are also only able to cover a few months of data in 2009. In contrast, our study has contained four years of data at 5-minute intervals for nine series, covering three types of instruments across three markets.

12. The reason for the inclusion of iShare and Lyxor ETFs is that these come under the top five largest providers of ETFs, and taken together, they representing 76.1% of the market share. The five largest providers of ETF include iShares, db xdb ETC, Lyxor AM, UBS ETFS, and Amundi ETF.

    (https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-services/performancemagazine/articles/lu_growth-etf-in-europe-012017.pdf)

13. The empirical applications of the common factor weight method can be found in Booth et al. (1999), Chu et al. (1999), and Harris et al. (2002b).

14. $S_{ij} = T^{-1} \sum_{t=1}^{T} R_{it} R_{jt}^{'}$, $i, j = 0, 1$. It captures the residuals R from regressing ΔP_t and $P_{t\text{-}1}$ on $(\Delta P_{t\text{-}1,} \dots, \Delta P_{t\text{-}q+1})$, respectively.

15. In some cases, the lower bound constitutes only one-tenth (or even less) of the upper bound.

16. https://www.ft.com/content/d12ac93c-a507-11e6-8b69-02899e8bd9d1

17. https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-services/performancemagazine/articles/lu_growth-etf-in-europe-012017.pdf

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