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Do ETFs lead the price moves? Evidence from the major US markets

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Abstract

In this paper, we study relative price discovery for three major US indices, their futures and exchange traded funds (ETFs) using intra-day price movements from 2003 until 2013. The methodologies employed in our analysis include information share (IS), permanent and transitory decomposition (PT), and weighted price contribution (WPC). The results from PT indicate that for each index ETFs have taken over the role of price discovery from futures contracts; while the results from WPC suggest that the spot markets lead price movements, which in turn implies the ETFs may have adjusted prices actively to pre-market information and activities.

Key Words: Price Discovery, Information Share, ETFs, Permanent and Transitory Decomposition, Weighted Price Contribution

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1 Introduction

In recent years, especially since the financial crisis in 2008, exchange traded funds (ETFs) have become very actively traded. By the end of 2016, the total asset value under management exceeded \$3 trillion US dollars, and the daily trading volume of the biggest ETF, State Street's SPDR S&P 500 was over \$14 billion US dollars¹, outperforming the daily trading volume of Apple stock at \$3 billion US dollars. From a small beginning 20 years ago, ETFs now account for nearly 50% of stock trading in the United States. As the trading of exchange traded funds (ETFs) has become progressively more dominant in many financial markets, this is likely to have had an impact on price discovery in the underlying market. The market reaction to Donald Trump's election in the United States in November 2016 was a large upward movement for stocks and downward movement for bonds. In the two weeks between the November 8th election and the Thanksgiving holiday, nearly \$50 billion stock ETFs were bought and roughly as much capital withdrawn from fixed income securities². Whether ETF trading was behind these stock price movements, or, equivalently, whether ETFs have taken on the role of price discovery in the underlying market is open to question. The role of ETFs in price discovery in stock markets has not been explored in an extensive manner and the few studies conducted have found different results. Tse et al., (2006), Schlusche (2009) and Theissen (2012) all find that despite the introduction of ETFs, futures still lead in terms of price discovery. In contrast, studies by Chou & Chuang (2006), Ivanov et al. (2013) and Deville et al. (2014), have found evidence to suggest that the price discovery lead of index futures has been weakened by the introduction of ETFs. They also find that with the introduction of ETFs, spot markets have become more informative and have

¹ Data Source: <https://www.ft.com>

² <https://www.ft.com>

increasingly contributed to price discovery. In order to contribute to the debate on the role of ETFs in price discovery, we undertake an extensive study of price discovery for three major US price indices with a focus on whether ETFs have become the dominant vehicle for price discovery over spot indices or futures. In particular, we study the three major US stock market indices (S&P 500, NASDAQ and Dow Jones), their futures³ and ETFs using a large-scale dataset covering eleven years of intra-day price observations. This is particularly important as the introduction of new instruments into the trading would be expected to have impact on existing price discovery structure. In the literature, there has been a good body of studies on discovery role between spot and futures contracts. The studies on the ETFs' impact to the change of price dominance are limited⁴ and there are only two studies which model the price discovery dynamics across spots, futures and ETFs but over small datasets (see Ivanov et al., 2013 and Chou and Chuang, 2006). In order to provide robust conclusions, we utilize three different methods for the examination of price discovery namely, Hasbrouck (1995) information share (IS), Gonzalo and Granger (1995) permanent and transitory decomposition (PT), and Barclay and Hendershott (2008) weighted price contribution (WPC). Both Hasbrouck (1995) IS and Gonzalo & Granger (1995) PT methods are widely employed in the literature in examining price discovery of the same asset traded on different markets. They are formed on a vector error correction model (VECM), with an aid of a decomposition process in their procedures. Each of these two approaches, however, has its unique features and advantages. The IS method decomposes the innovation terms in VECM and tracks price changes via the permanent component of the innovation. By comparing the speed of adjustments of the innovation terms, the contributions to the price discovery processes are effectively obtained. The PT method, on the other hand, decomposes price or return series into one permanent and one transitory component and uses the cointegration vector of the VECM to calculate the permanent component coefficients. These coefficients are decomposed from price series, and through changes in the

³ For the futures, we include both floor-traded and electronically traded contracts.

⁴ See Hasbrouck (2003), Tse et al. (2006), Chou and Chuang (2006) and Ivanov et al. (2013).

permanent component the contributions to the price discovery processes are determined. The Barclay and Hendershott (2008) WPC method, on the other hand, takes a different approach to that of the Hasbrouck (1995) IS or Gonzalo and Granger (1995) PT method. In their original paper, the WPC method is used to empirically determine the information content from trading in the pre-open period, and its influence on price discovery. The WPC method itself is a simple price weighted contribution metric to measure price discovery. Here the changes of price returns in the same period of a day for each day in the sample are weighted and consequently the price contributions of every period within that day are calculated.

The use of three methodologies not only provides a robust check of the role of ETFs in price discovery, but also forms a nice comparison among the modeling techniques. This, subsequently, forms our second contribution to the literature as our paper, to our best knowledge, is the first study to employ all three methods to study this issue. Further, our study looks at three major US indices for over an 11-year period at intra-day level. In contrast to majority literature utilizing a few-months' worth of data, we claim that our paper forms the first full market study covering multiple assets, multiple markets and long period to examine whether the price discovery role of ETFs is consistent across different markets. Third, we employ the most extensive data set of all studies so far, consisting of 11 years of 1-minute intra-day observations ending in 2013.

Our findings support the view that ETFs have become the lead vehicle for price formation in all three US markets studied and the results from all three price discovery methodologies are consistently support it. Such finding is also consistent with Chou and Chuang (2006) and Ivanov et al. (2013). This also would be the results we would expect to have because ETFs show strong trading performance in terms of both trading speed and volumes; thus, the information transmission through such vehicle would be more prominent than other less-traded and/or slowly-traded assets. In addition, the contributions to price discovery associated with the spot markets

appear to have increased remarkably compared to previous studies. This, we suggest, is based on the fact that active trading of ETFs leads to trading of the underlying components of the corresponding indices in order for the ETFs to track and replicate the underlying index. In other words, the results in our study support the view that with the introduction of ETFs the spot index itself has also become more active in terms of price discovery.

The remainder of the paper is organized in the following fashion. Section 2 examines the existing literature in the area of price discovery both from a theoretical and empirical perspective. Section 3 explains the data and methodologies employed in our paper. Section 4 presents the empirical findings of our study and section 5 concludes.

2 Literature Review

2.1 Do the new financial instruments play a major informational role in price discovery? – Summary findings from the existing literature

A number of studies have examined relative price discovery among major US indices and their traded derivatives. Early lead-lag studies on the relationship between the S&P 500 index and floor traded index futures, for example, Kawaller et al. (1987), Stoll and Whaley (1990) and Chan (1992) report a dominant role in price discovery for the S&P 500 futures. Later studies have used the Hasbrouck Information Share (IS) and/or Gonzalo-Granger PT methodologies to provide new insights on the price discovery process. Kurov and Lasser (2004), examined price discovery between the S&P 500 futures and S&P 500 E-mini as well as the NASDAQ 100 futures and NASDAQ E-mini. Applying the (IS) method to a period in 2000 they found both E-mini contracts lead price discovery compared to the regular futures contracts. 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 from 1997 to 2001. They used both (IS) and (PT) methodologies

though the two methodologies give very similar results. They found both E-mini index futures and regular index futures contribute to the price discovery process, however the contribution of E-mini futures is greater than that of the regular index futures

Hasbrouck (2003) studied the dynamics of price discovery using both intraday quotes and trades for the period March to May in 2000 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 of regular floor-traded futures, E-mini futures and SPDR ETFs. One of the main findings was that, for the S&P 500 and Nasdaq100 indices E-mini dominates price discovery over spot indices, with the contract itself possessing the dominant information share that accounts for up to 90% of the price discovery. Here, the paper finds that despite the introduction of ETFs, futures still lead in terms of price discovery. However, it should be noted that ETFs were not as heavily traded in the early part of the 2000s compared to the latter part of the decade.

Tse et al. (2006) studied both intraday quotes and trades for the period May to July in 2004 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 contribute most to price discovery, followed by ETFs and then indices, with little or no contribution from floor-traded futures.

Chou and Chuang (2006), however, conducted similar analysis for the Dow Jones, S&P 500 and NASDAQ indices and related derivatives over a period from October 2000 to April 2001 and found that ETFs lead price discovery after ETFs are quoted using decimal instead of the fraction method. Ivanov et al. (2013) used both IS and PT

methods to study indices, index futures and index ETFs across the DJIA, S&P 500, S&P 400, NASDAQ 100 and Russell 2000 from January 2000 to December 2012. Although the study was not conducted at the intra-day level but at the daily level, it generated similar evidence that the introduction of ETFs weakens the dominance of the index futures in revealing the underlying price updating process.

Other studies have examined the price discovery role of ETFs for commodity markets. Ivanov (2013) examined price discovery between ETFs, futures and commodity spots for gold, silver and oil using the IS method from January to August in 2009. The study found that with the introduction of ETFs, the futures lose their dominance in price discovery because ETFs incorporate information into the underlying formation of prices much faster than other asset classes during trading hours.

One criticism that can be made of many of the studies cited above is that their results are based on an analysis of a short period of time, in some cases just a few months. It could be that the period considered was one of high or low liquidity for one of the contracts or a period soon after the introduction of a contract. The validity of these studies is, therefore, dependent on the time period of the data used. This study overcomes this deficiency by utilizing a long (11-year period) run of intraday data.

2.2 Classical empirical methodologies used to study the price discovery processes – A consideration of their unique features and drawbacks

Price discovery across assets and/or markets is one of the fundamental topics in the finance literature. During the 1980s, a number of pioneering methods for the examination of price discovery have emerged with the majority of them rooted in examining the long-run relationship among price or return series for related financial assets in different markets. In these cases, the VECM or vector autoregressive (VAR) representation of the data resulting from multivariate regression analysis is involved to test for the existence of the long-run relationship. One of the earlier literatures in

the area, for example, Kasa (1992) found the error correction and co-integrating coefficients through a process of common factor decomposition in a VECM representation of the data. It decomposes the price-updating process into one permanent and one transitory component. Typically, the permanent component drives the long-run cointegrating relationship among time series as the common factor. The orthogonal complements reflect the common factor and are calculated as a weighted average of the permanent component⁵. Kasa (1992) applied the method to the major stock market indices across U.S., Japan, England, Germany, and Canada, using monthly price data from January 1974 to August 1990. Then the significance of the permanent component indicates the presence of a single common trend, which drives the co-movements of those stock markets. The results on transitory components suggest that the Japanese market is the most significant one while the Canadian stock market is the least driven by the common trend.

Although the common factor decomposition method provides a clear indication of price discovery of the dominant market, Gonzalo and Granger (1995) argued that the transitory components may partially, at the same time, contain the accumulation of price changes that are actually driven by the permanent components (also see Stock & Watson, 1988). Gonzalo and Granger (1995) went on to incorporate the Kasa (1992) decomposition method into their work by assuming the permanent component to be non-stationary but the transitory component to be stationary. They then let the permanent component carry the price changes over time and further used Johansen and Juselius (1990) cointegration test to test for the long-run co-movement structure. Based on the VECM further price discovery can be identified through the orthogonal complements of the vector error correction coefficients. This method, both initiated and developed by Gonzalo and Granger (1995) is often referred as the common factor component share or permanent-transitory decomposition.

⁵ The orthogonal complements are the orthogonal vector of the error vector in the VECM.

Whilst Gonzalo and Granger (1995) takes the error correction coefficient as the contribution by each market to the common factor, Hasbrouck (1995) uses the variance of the common factor innovation to measure the contribution by each market to this variance, which is the information share (IS). The study suggested that the underlying pricing process contains a permanent component that drives its evolution. Part of the variance of the pricing process is the common factor that reflects this permanent component and it may be measured using the information share. If we take the covariance matrix of the underlying pricing process and the moving average of the VECM to capture the price evolution, the IS measure may be written as the percentage of total price movement embedded in both the updating processes and time-varying changes of the correlation vectors. Clearly, the correlations between the underlying price evolution affect the IS measure, especially when we calculate the upper and lower bounds of it. Usually, the final measure of IS is taken as an average of the upper and lower bounds⁶.

The two classical methods we discussed so far, namely Gonzalo and Granger (1995) PT and Hasbrouck (1995) IS, are traditionally regarded as close to each other. Baillie and Bollerslev (2002) argued that the permanent transitory component in Gonzalo and Granger (1995) is proportionally equivalent to the key coefficients in the IS model of Hasbrouck (1995)⁷. When the empirical results on minute data of mid-quotes in five groups of Nasdaq participants including ECNs, wholesalers, wire houses, institutional brokers and others over a one-month period were examined, they suggested that if the sum of moving average coefficients from the IS calculation is replaced with the PT results, the test results remain unchanged in terms of which of these series dominates

⁶ The IS method may not generate a unique measure of the information share. Instead, an upper and a lower bound can be obtained as alternatives.

⁷ The IS method uses the vector of coefficient by calculating the sum of all coefficients in an infinite vector moving average model transformed from the VAR. Baillie and Bollerslev (2002) argue that such a coefficient vector is proportionally equal to that from the PT method of Gonzalo and Granger (1995) if identical data sets are applied and tested.

the price discovery. This result indicated that both methods are closely related to each other and the key difference is that the IS method picks up the residual correlations in VECM whereas the PT method does not. When VECM residuals are uncorrelated, both methods are equivalent. If the correlation is marginally significant (not highly correlated), the IS method proposed by Hasbrouck (1995) still holds and provides appealing results with strong economic implications. However, when the residuals from VECM become highly correlated, the IS method could serve as one of the optional methods.

Some research, however, suggested that the PT method is more robust as it does not incorporate residuals of the VECM. De Jong (2002) applied both the PT and IS methods to the simulated data of Hasbrouck (2002) to test the parameter estimates of a one-way price adjustment hypothesis. They found that the IS method, due to the restrictions of the upper and lower bounds, causes biased results when the innovations of the price series are highly correlated with each other. The Gonzalo and Granger (1995) PT method, however, is found more accurate in revealing the overall price discovery. Madhavan et al. (1997), however, proposed a structural model to determine the permanent impact of order flow innovation. They argued that a comparison of the adverse selection parameter and the order processing cost parameter serves as a useful validation to the PT method.

Lien and Shrestha (2009) attempted to address the bias in Hasbrouck (1995) and proposed a modified IS measure (MIS) that is free from the requirements of upper and lower bounds. They decomposed the error covariance matrix into a standard deviation diagonal matrix and an eigenvector so that factorization can be achieved to eliminate the excessive upper and lower bounds. For robustness purposes, they run both IS and MIS over price indices including FTSE 100, S&P 500 and Tokyo Stock Index at the 5-minute level from March to September 2006. Their results showed that the inclusion of the upper/lower bounds does not affect the results and found that the futures lead price movement over the spot. Flad and Jung (2008) investigated both the

short-term and long-term relations between the DAX and DJIA indices. They applied Kasa (1992) decomposition, Gonzalo and Granger (1995) PT and Hasbrouck (1995) IS methods. They found that the DJIA contributes over 95% of the common factor between the two markets under study. In addition, they attempted to simplify the calculations for decomposition and PT methods particularly in the case of bivariate (for example, two markets) settings.

2.3 Alternative empirical methodologies used in the literature to reveal the price discovery processes

In addition to the traditional methodologies used to reveal the price discovery processes, some alternative approaches have been proposed in the literature. For example, So and Tse (2004) used a multivariate generalized autoregressive conditional heteroscedasticity (M-GARCH) model in conjunction with the IS and PT methods to explore the minute-by-minute data from Hang Seng Index, Hang Seng Index futures, and a tracker fund. Their results suggested that the futures markets contain the most information, followed by the spot. The tracker fund does not contribute to the price discovery process. In addition, the three markets exhibit spillover effects based on the M-GARCH results, indicating that their second moments are linked to each other. Schlusche (2009) examined the futures and ETFs of the DAX index, using Schwarz and Szakmary (1994) common factor weights approach, which is calculated using the error correction term of VECM.⁸ The study indicated that futures, instead of the ETFs, drive price formation in the main. Theissen (2012) used a threshold error correction model⁹ to examine price discovery among

⁸ The method on which Schwarz and Szakmary (1994) is based is different from the IS or PT methods where it contains no decomposition process in the error variance. In addition, the method itself appears applicable to resolve price discovery involving two time series.

⁹ Fundamentally, this method is very similar to that of Gonzalo and Granger (1995). However, the method is applicable on two variables only.

ETFs, futures and the underlying DAX spot index pair by pair¹⁰. The main findings were that the futures contracts lead price discovery and the presence of arbitrage opportunities¹¹ greatly affects the dynamics of price discovery results.

Barclay and Hendershott (2008) introduced a weighted price contribution (WPC) method to examine price discovery. The study used daily returns to generate a weighting mechanism, and set the sub-period returns within a day proportional to it as indicators of contributions to price changes. They calculated the contributions of the NASDAQ index from 1993 to 1999. Each day covers the time when the market is open for both trading and non-trading hours and is partitioned into four sub-periods: pre-open time, post-open time, overnight and trading time. They found that the WPC is the highest during trading hours. However, they also find with the increase in trading volumes during pre-open times over the sample period, pre-open period price discovery contribution dominates the open period price discovery. In this study we modify the WPC method of Barclay and Hendershott (2008) to reveal the price contributions among different time-periods of a day from the same asset. Although the WPC method itself was not proposed to reveal the ‘dominant’ market in each group of the instruments as the PT or IS method does, we argue the underlying index, futures and ETFs reflect the same information, thus the leading market should be the market that adjusts its price the quickest. Therefore, this leading market should be the one that has the highest value of WPCs during the early time-period of a day. Thus, we provide an additional approach to analysing price discovery to provide a robustness check on the results from the application of IS and PT.

¹⁰ The method itself is constrained to a bivariate approach. The author runs the model over spot and futures; and then over futures and ETFs, respectively.

¹¹ A dummy variable was introduced to represent the presence of arbitrage opportunities. It is set to 1 when there is arbitrage and 0 otherwise.

3 Data and Methodology

3.1 Data

In this study, we accessed Thomson Reuters Tick HistoryTM and collected intraday prices at a 1-minute frequency over an eleven-year period from January 2003 to December 2013. We focused our attention on primary equity indices, equity index futures (both floor and/or electronic traded) and ETFs across the major US stock markets. We divided them into three groups: 1) S&P group including the S&P 500 spot index (SPX), floor-traded and electronic-traded futures (SPc and ESc) and three ETFs (SPY, IVV, VOO); 2) NASDAQ group containing the spot index (NDX), electronically traded futures (NQc) and ETF (QQQ); and 3) Dow Jones group of the spot index (DJA), electronic futures (DJc) and ETF (DIA)¹². Prior to data cleaning process, each of these twelve price series contains 5,781,600 observations over 2761 trading days during eleven years. However, the VOO (Vanguard ETF tracking S&P) and DJc have nearly 50% of the data missing over the sample period and thus we excluded these two financial instruments from our analysis, which left us with ten series (see Table 1)¹³. We further cleaned our dataset and resolved the typical missing data problems due to technical issues from raw data collection or structural problems. Excessive data were recorded during non-trading periods following Dacorogna et al. (2001) and Falkenberry (2002).

The three groups of assets are traded on various venues from 9:30 am to 4 pm EST during the weekdays except for nine public (non-trading) holidays and three early-close trading days (trading closes at 1 pm on these days) for each year¹⁴. During

¹² In order to be more efficient with the time series references, we use the Reuters Instrument Codes (RICs) to indicate them. In the remaining sections of the paper, the time series are referred with the RICs.

¹³ With such a setting, S&P and NASDAQ cover spot, futures and ETFs; while Dow Jones only covers spot and ETF for further data cleaning and modelling.

¹⁴ The public holidays include the New Year's Day, Martin Luther King Day, Washington Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving and Christmas. The three days when trading finishes early at 1pm are the day

our data cleaning process, any data falling into the non-trading time (including the pre-market time) were deleted. This has resulted in a total of 4,702,135 non-trading periods being excluded from the sample. The majority of the missing data are spread across the entire sample period and this could be due to the technical problems in recording of the data. For NASDAQ, most of the missing data records are in the years of 2003 and 2004 and so the usable data points of NASDAQ series start from the year of 2005 with a size of 888,873.

We then backfilled the missing data using the nearest available prices. The details of the number of observations that were backfilled are:

- 1) S&P group: 992,622 backfills for ETFs, which included IVV, SPX, and VOO; 398,366 for futures, which contained SPc, ESc and spot index (SPX);
- 2) NASDAQ group: 264,335 for ETF (QQQ); 278,616 for futures (NQc) and 264,337 for index (NDX);
- 3) Dow Jones group: 180,471 for ETF (DIA); 592,124 for futures (DJc) and 171,587 for spot (DJI).

In the literature, there are various methods that deal with the outliers. Verousis and Gwilym (2010) suggest deleting the outliers, which are defined as excessive price changes above a 5% threshold. There are debates in the literature utilizing high frequency data as to whether these price changes should be deemed as outliers, especially if they occur right at the beginning of the trading on a day with lots of volatility. The information carried by these ‘outliers’ affect trading strategies and cause arbitrage or change price discovery of the continuous trading process (see Brownlees and Gallo, 2006). We believe that any data, especially those, right after the market opens to trade, carry enormous amount of information which in turn would

before the Independence Day (July 03), Black Friday (the day after the Thanksgiving) and Christmas Eve.

indicate the trend in the price adjustments and trading behavior (for instance, price or volume alteration; buy or sell adjustments). Therefore, to prevent the loss of important information, we have kept all the data instead of taking out the outliers at the start of each trading day. After all the data cleaning has taken place, for NASDAQ, the number of usable data points is 888,873; and for the other nine series, the individual dataset is 1,079,465 points. In this respect, our study represents the most extensive dataset so far utilized to facilitate the examination of price discovery on a cross-asset and cross-market setting.

Our clean data sample contains ten price series and covers the year (2008) of the financial crisis. Therefore, it is intriguing to see whether structural breaks around the period of the crisis affect price discovery. In this respect, we partitioned the data into three sub-periods: pre-crisis period (2003-2006), crisis period (2007-2008) and post-crisis period (2009-2013).¹⁵ The descriptive statistics are reported in Table 1.

¹⁵ We treat the problems at Bear Stearns in the US in 2007 and Northern Rock in the UK in mid-September in 2007 as a sign of the beginning of the 2008 financial crisis and thus included the year of 2007 in the crisis period.

Table 1: Descriptive Statistics of Ten Series

Table 1 reports the descriptive statistics for the ten clean price series (DJI, DIA, NDX, NQc, QQQ, SPX, SPc, ESc, IVV and SPY) associated with Dow Jones, NASDAQ and S&P. The sample period can be partitioned into sub-periods according to the 2008 financial crisis: pre-crisis (2003-2006), crisis period (2007-2008) and post-crisis period (2009-2013).

	Type	Dow Jones		NASDAQ			S&P				
		Index	ETFs	Index	Futures	ETFs	Index	Futures	Futures	ETFs	ETFs
	RIC	DJI	DIA	NDX	NQc	QQQ	SPX	SPc	ESc	IVV	SPY
Pre-Crisis	Mean	10318.54	103.26	1605.96	1613.44	39.53	1153.23	1154.77	1154.72	115.7	115.59
	S. Dev	974.95	9.68	94.71	96.1	2.31	136.12	138.17	138.11	13.59	13.5
	Median	10468.83	104.74	1589.79	1595	39.15	1174.31	1176	1176	117.6	117.53
	Max	12528.36	125.13	1823.91	1843.13	44.84	1431.65	1444.5	1443.63	143.86	143.2
	Min	7417.9	74.38	1394.9	1398.25	34.38	789.03	792.2	792.13	1	79.42
	No.obs	394252	394252	196915	196915	196915	394252	394252	394252	394252	394252
Crisis	Mean	12213.11	122.12	1821.64	1830.06	44.8	1348.9	1352.87	1352.83	135.26	134.99
	S. Dev	1499.27	14.96	251.69	254.19	6.19	188.57	190.42	190.4	18.84	18.81
	Median	12567.59	125.63	1866.06	1876.13	45.89	1407.31	1410.5	1410	141.02	140.74
	Max	14195.3	141.92	2238.98	2250.63	55.03	1575.91	1583.8	1583.88	157.77	157.5
	Min	7469.97	74.72	1019.5	1031.13	25.14	742.12	746.15	746.5	74.69	74.6
	No.obs	196375	196375	196375	196375	196375	196375	196375	196375	196375	196375
Post-Crisis	Mean	11891.26	118.82	2283.14	2280.43	56.06	1274.94	1271.66	1271.73	128.21	127.67
	S. Dev	2160.47	21.5	564.23	562.52	13.77	245.77	245.15	245.15	24.75	24.55
	Median	12057.38	120.4	2308.62	2305.13	56.69	1278.92	1275.5	1275.88	128.51	128
	Max	16582.73	165.45	3591.71	3585.13	87.99	1849.13	1841.15	1841.38	185.72	184.64
	Min	6472.07	64.8	0	1047.13	25.66	666.92	672	672	67.28	67.16
	No.obs	495583	495583	495583	495583	495583	495583	495583	495583	495583	495583
Whole Sample	Mean	11378.61	113.77	2031.17	2033.17	49.91	1244.13	1243.92	1243.92	124.94	124.61
	S. Dev	1880.07	18.7	527.85	524.38	12.89	214.78	215.14	215.13	21.58	21.41
	Median	11110.67	111.1	1889.37	1893.63	46.47	1242.98	1243.65	1243.88	124.83	124.49
	Max	16582.73	165.45	3591.71	3585.13	87.99	1849.13	1841.15	1841.38	185.72	184.64
	Min	6472.07	64.8	0	1031.13	25.14	666.92	672	672	1	67.16
	No.obs	1086210	1086210	888873	888873	888873	1086210	1086210	1086210	1086210	1086210

Our empirical analyses involve the use of permanent transitory decomposition and information share methods. These methods are constructed on a vector error correction model (VECM), which requires non-stationarity, or equivalently, a single unit root $I(1)$ of the price series. In order to check for the non-stationarity condition of the data, we performed the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) unit root tests on all price series under each of the three markets over our classified

time periods (see Table 2). The unit root tests were carried out on levels and then on first differences of the series. The results confirm that all price series under our study are integrated of order 1.

Table 2: Augmented Dickey Fuller and Phillips-Perron Unit Root Tests

Table 2 reports the unit root test results of all series as both the PT and IS methods are constructed on a vector error correction model (VECM), which requires non-stationarity of the price series. We perform the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests on levels and on first differences of all series. The results confirm that all of them are integrated of order 1 in over the classified sample periods.

	Type RIC	Dow Jones		NASDAQ			S&P				
		Index DJI	ETFs DIA	Index NDX	Futures NQc	ETFs QQQ	Index SPX	Futures SPc	Futures ESc	ETFs IVV	ETFs SPY
Pre-Crisis	Lvl ADF	0.768	0.7637	0.5864	0.6078	0.5564	0.7754	0.7764	0.7718	0.7401	0.7536
	Lvl PP	0.7552	0.7587	0.6098	0.6201	0.5961	0.7615	0.7808	0.7762	0.1156	0.7524
	1st ADF	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	1st PP	0.0001	0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0	0.0001
Crisis	Lvl ADF	0.9463	0.9395	0.9359	0.9013	0.931	0.9601	0.9384	0.9427	0.9639	0.9623
	Lvl PP	0.9409	0.9407	0.9436	0.905	0.9445	0.9655	0.9429	0.9459	0.9638	0.9654
	1st ADF	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	1st PP	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Post-Crisis	Lvl ADF	0.9384	0.9431	0.7843	0.932	0.9295	0.9503	0.9404	0.9405	0.9466	0.955
	Lvl PP	0.937	0.9356	0.4105	0.9302	0.9319	0.9515	0.9423	0.9418	0.9487	0.9477
	1st ADF	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	1st PP	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Whole Sample	Lvl ADF	0.8407	0.8446	0.9513	0.9913	0.9944	0.8395	0.767	0.769	0.8264	0.8305
	Lvl PP	0.8325	0.8285	0.9915	0.9915	0.994	0.8329	0.7801	0.7747	0.8003	0.8208
	1st ADF	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	1st PP	0.0001	0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0	0

3.2 Methodology

In this section, we discuss the various measures of price discovery employed by our study. We confine our discussion to the PT, IS and WPC methods in estimating the contributions of each index/product to the price discovery of the common factors. Both PT and IS methods are based on the existence of q co-integrated $I(1)$ price series defined by the q -dimensional price vector $P_t = (p_{1t}, p_{2t}, \dots, p_{qt})$. In our paper $q = 2, 3$,

or 5 that corresponds to three groups of data based on the underlying equity indices, namely S&P 500, NASDAQ and Dow Jones. In particular, when $q = 2$, $P_t = (DJI, DIA)$; when $q = 3$, $P_t = (NDX, NQc, QQQ)$; and when $q = 5$, $P_t = (SPX, SPc, ESc, IVV, SPY)$. 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:

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

where $\Pi = \alpha \cdot \beta'$, A_j is a $q \times q$ 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:

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

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

Both IS and PT methods are based on the information embedded in the matrix Π of equation (1). In particular, they involve 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 IS 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:

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

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

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

The matrix $\Psi(1)$ in Eq. (4) is the sum of the moving average coefficients, where $\Psi(1) = I + \theta_1 + \theta_2 + \dots$, 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 IS. Denoting $\psi = (\psi_1, \psi_2, \dots, \psi_q)$ as a common row vector in $\Psi(1)$ and τ as a column unit vector, Eq. (4) may be re-written as:

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

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

$$\frac{\psi_j^2 \Omega_{jj}}{\psi\Omega\psi'} \quad (6)$$

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:

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

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

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:

$$\frac{\gamma_j^2 \Omega_{jj}}{\gamma \Omega \gamma'} \quad (8)$$

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

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_l (Eq. 10) and IS_q (Eq. 11), respectively:

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

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

Baillie and Bollerslev (2002) suggest that the midpoint of these two bounds may be used as a measure of price discovery for each market.

The PT method of Gonzalo and Granger (1995) decomposes the original price series into one permanent component $I(1)$ and one transitory component $I(0)$ following Stock and Watson (1988):

$$P_t = B_1 f_t + \tilde{P}_t \quad (12)$$

where B_1 is a loading matrix, f_t is a vector of common factors (permanent component) and P_t is a vector of transitory component. The method defines the common factor as a linear combination of the variables P_t , such that $f_t = \Gamma P_t$ where Γ is the common factor coefficient vector. The common factor coefficient vector Γ is orthogonal to the error correction coefficient vector α in Eq. (1), which may be denoted by $\alpha_{\perp} = (\gamma_1, \gamma_2, \dots, \gamma_q)$.¹⁶

The maximum likelihood estimator for the common factor from Johansen and Juselius (1990) procedure is then $\hat{\alpha}_{\perp} = (\hat{m}_{r+1}, \dots, \hat{m}_q)$, where r is the number of co-integrating relationships in the system. As previously noted, the permanent component is a linear combination of the variables in the cointegrated system, where α_{\perp} gives the common factor weight for each variable Γ . A variable with greater weight in the

¹⁶ Following Johansen and Juselius (1990) we concentrate on matrix Π and, as in Gonzalo and Granger (1995), regress ΔP_t and P_{t-1} on $(\Delta P_{t-1}, \dots, \Delta P_{t-k})$ respectively using Ordinary Least Squares (OLS) on a sample of T observations where k is the number of lags in Eq. (1). The residual product matrices are given by:

$$S_{mn} = T^{-1} \sum_{t=1}^T R_{mt} R'_{nt} \quad (13)$$

$$m, n \in \{0, 1\}$$

where R_{0t} and R_{1t} are the residuals obtained from the two OLS regressions.

The maximum likelihood estimator of α_{\perp} is found by solving Eq. (14) for eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > \dots > \hat{\lambda}_q$ and eigenvectors $\hat{M} = (\hat{m}_1, \hat{m}_2, \dots, \hat{m}_q)$ that were normalized such that $\hat{M}' S_{00} \hat{M} = I$:

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

linear combination contributes more than other variables to the revelation of the common factor and is therefore regarded as the leading or ‘dominant’ market. For simplicity, we normalize the common factor weights such that they add up to 1¹⁷ and use these as PT measures for each market. The method is then repeated for each month in each of the indices for dynamic results.

The weighted price contribution (WPC) method proposed by Barclay and Hendershott (2008) takes a more straightforward approach to the calculations of price discovery, when compared to the IS or PT method. In order to adapt the WPC method to our unique data sets, some adjustments to the method of Barclay and Hendershott (2008) have been made. We first calculate the return of the price series according to Eq. (15):

$$\begin{aligned} RET_k &= \ln(P_k) - \ln(P_{k'}) \\ RET_{k,t} &= \ln(P_{k,t}) - \ln(P_{k,t-1}) \end{aligned} \tag{15}$$

where RET_k is a vector of daily returns that contains all indices’ returns on day k .

P_k is the close price of day k and $P_{k'}$ is the open price of day k . $RET_{k,t}$ is a vector of minute returns of time t in day k . The purpose of Barclay and Hendershott (2008) WPC method is to discover price contributions during each period of a day. In their original model, the daily returns are calculated as the difference between the end-of-day prices of day k and day $k-1$. In our study, as those non-trading time data are not included and without non-trading time data, the end price of day k will be different from the open price of day $k+1$, which could lead to false results in the next step of the WPC method. In this respect, we switch to the open price when calculating daily returns.

Using these returns, the WPCs are given by:

¹⁷ The normalization ensures that the PT measures sum to unity, similar to the case of IS.

$$WPC_t = \sum_{k=1}^{T'} \left(\frac{|RET_k|}{\sum_{k=1}^{T'} |RET_k|} \right) * \left(\frac{RET_{k,t}}{RET_k} \right) \quad (16)$$

where T' is the period of the test. In our study, T' is the number of days in a month. The first item in the right-hand side of Eq. (16) is a weighting factor for each day in period T' . The second item is the relative contribution of the return at time t on day k . WPC_t is a weighted sum of price contributions at time t of each day in the given time period T' . The nature of the WPC method is to discover the price contributions among time-periods of a day. Thus, it is not suitable to compare the results from it with those from the PT method, nor is it capable of revealing the ‘dominant’ market in each group of the data. However, our data sets are based on the same underlying index, where the futures, ETFs and spot prices are reflecting the same information, thus the leading market should be a market that adjusts its price in the quickest manner. Therefore, this leading market should be the one that has the higher value of WPCs during the early time-period of a day.

4 Empirical Results

4.1 Component Share Results

To begin our analysis, we perform the Johansen and Juselius (1990) Trace Test to assess the cointegrating rank of the long-run Π matrix. The results in Table 3 show that for each of the three groups, namely, Dow Jones, NASDAQ and S&P, all price series – DIA and DJI in Dow Jones; QQQ, NQc and NDX in NASDAQ; SPX, SPc, ESc, IVV, and SPY in S&P are cointegrated with at least one cointegrating vectors.

Table 3: Johansen and Juselius (1990) Trace Test

Table 3 shows the Johansen & Juselius (1990) trace test result to determine the cointegrating rank of the long-run π matrix. The results suggest the equity indices, ETFs and index futures grouped under Dow Jones, NASDAQ and S&P are all cointegrated. In each separate market, there, at least, exists one cointegrating vector (DIA and DJI in Dow Jones; QQQ, NQc and NDX in NASDAQ; SPX, SPc, ESc, IVV, and SPY in S&P).

Dow Jones	Cointegrating Vector	
	DIA	DJI
No. Lags	1	-0.010
10	Error Correction Vector	
Cointegrating Rank	Eq. DIA	Eq. DJI
1	-0.009	0.182

NASDAQ	Cointegrating Vector		
	QQQ	NQc	NDX
No. Lags	1	0	-0.022
5	0	1	-0.996
Cointegrating Rank	Error Correction Vector		
2	Eq. QQQ	Eq. NQc	Eq. NDX
	-6.07E-07	-0.0005	0.007
	-1.73E-06	-0.003	0.005

S&P	Cointegrating Vector				
	SPY	SPc	SPX	ESc	IVV
No. Lags	1	0	0.059	-0.026	-1.327
10	0	1	-0.005	-1.017	0.217
Cointegrating Rank	Error Correction Vector				
2	Eq. SPY	Eq. SPc	Eq. SPX	Eq. ESc	Eq. IVV
	-0.003	0.069	-0.009	0.0639	0.029
	0.000	-0.005	0.0009	0.0129	-0.000

Table 4 presents a summary of the estimated permanent and transitory components of the ten time series for the Dow Jones, NASDAQ and S&P groups. Since the PT result is not bounded between 0 and 1, unlike the IS measure, it can take on a very large

value when we normalize the result and this may possibly impact upon the average value of the PT. Hence, we also record the number of periods of leading for each asset in the three designated markets as a validation to the PT results (see Table 4).

Table 4: Monthly Component Share (PT) Results

Table 4 presents the estimated permanent and transitory components of the 10 time-series grouped under Dow Jones, NASDAQ and S&P. We also record the number of periods each asset leads in the three markets to re-confirm the PT results.

		Dow Jones		NASDAQ			S&P				
	Type	ETFs	Spot	ETFs	Futures	Spot	ETFs	Futures	Spot	Futures	ETFs
	RIC	DIA	DJI	QQQ	NQc	NDX	SPY	SPc	SPX	ESc	IVV
Summary Statistics	Mean	0.9552	0.0448	1.0265	-0.0257	-0.0007	1.0744	-0.0127	0.0947	-0.0495	-0.1068
	Max	4.3719	3.2772	3.7052	0.3303	1.2487	11.4795	0.8802	14.138	0.7409	12.8373
	Min	-2.2772	-3.3719	-0.0608	-1.9415	-2.7212	-11.7316	-1.1398	-8.7408	-3.8638	-10.836
No. of Leading Periods	Whole	119/132	13/132	100/108	0/108	8/108	61/132	0/132	33/132	0/132	38/132
	Period	(90.15%)	(9.85%)	(92.59%)	(0.00%)	(7.41%)	(46.21%)	(0.00%)	(25.00%)	(0.00%)	(28.79%)
	Pre-Crisis	38/48	10/48	21/24	0/24	3/24	21/48	0/48	22/48	0/48	5/48
		(79.17%)	(20.83%)	(87.50%)	0.00%	(12.50%)	(43.75%)	(0.00%)	(45.83%)	(0.00%)	(10.42%)
	During	22/24	2/24	22/24	0/24	2/24	8/24	0/24	6/24	0/24	10/24
	Crisis	(91.67%)	(8.33%)	(91.67%)	0.00%	(8.33%)	(33.33%)	(0.00%)	(25.00%)	(0.00%)	(41.67%)
Post- Crisis		59/60	1/60	57/60	0/60	3/60	32/60	0/60	5/60	0/60	23/60
		(98.33%)	(1.67%)	(95.00%)	0.00%	(5.00%)	(53.33%)	(0.00%)	(8.33%)	(0.00%)	(38.33%)

Notes: From Table 4, we can see that: 1. PT results show that ETFs lead price discovery in the three groups. This has been validated through the estimated leading periods of ETFs in these groups; 2. The role of ETFs in the price discovery process for an index of stocks increases over time; 3. The spot markets have a greater role in price discovery before crisis with that role declining as time moves forward through the latter two sub-periods; and 4. Futures contracts play an insignificant role in price discovery.

As Table 4 shows, when the Dow Jones data set is considered, the PT result of the ETF market is as high as 0.9552 whilst that of the spot market is only 0.0448. The number of periods where the ETF market leads are consistent over the sample period, with 90.15% of the periods showing a lead by the ETF market and the remaining 9.85% showing a lead by the spot market. When we turn to the results for the NASDAQ data set, the average PT of the ETF market is 1.0265, showing an absolute dominant position in price discovery. Both the spot and futures markets in this data set are

below zero in terms of the PT, with a value of -0.001 for the spot and -0.0257 for the futures market. It is hard to assess which market is contributing more to the price discovery processes among spot and futures markets in this data set by looking at the overall average PT results. However, as 7.41% of the periods shows a lead by the spot market and none of the periods suggests a lead by the futures market, we conclude that for the NASDAQ dataset, the ETF market mainly leads the price discovery but for some periods, the spot market takes the lead.

For the S&P 500 group, we base our analysis on five markets, where we find that the leading market in price discovery is one of the ETFs (SPY) with a mean PT of 1.0744. The second most dominant market in terms of price discovery is the spot market with a mean PT of 0.0947. The futures contracts have mean PTs of -0.0127 (SPX) and -0.0495 (ESc). The other ETF contract on the S&P 500, IVV has a mean PT of -0.1068 indicating the least contribution. However, given the large variation in the PT measure over the whole sample it is perhaps more meaningful to examine price discovery contribution over each period (month) and then count the number of periods that a particular index/product leads price discovery. Examining the number of leading periods for each index/contract indicates a different result as the IVV ETF is the second largest contributor to the price discovery for the S&P 500 with 28.79% of the periods, which is slightly higher than the 25% for the spot market.

As our sample period covers 11 years starting from 2003 until 2013, it is interesting to examine whether there is a change in the leading market over time. Thus, we classified the sample period into three sub-periods, particularly taking into account the 2008 financial crisis as mentioned in Section 3.1. Looking at the number of leading periods over each of the three sub-periods we find, again, that ETFs dominate for each three markets. However, we also find that the spot markets played a greater role in price discovery before the crisis with that role declining as time move forward through the later two sub-periods. Futures contracts appear to have insignificant role in the price discovery process. This result supports the view that the role of ETFs in

the price discovery process for an index of stocks has increased over time.

Looking in more detail at the sub-period results for the Dow Jones group we find that in the pre-crisis period the ETF market is leading 79.17% of the periods and the spot market is leading 20.83%. From 2007 to 2008, ETFs lead for over 90% of the period and during the post-crisis period the ETFs lead for 98.33% of the time. For NASDAQ in the pre-crisis period the ETF market leads for 87.5% of the periods with 12.50% of the time the spot market leads. From 2007, the percentage of periods that ETFs lead increases steadily, reaching 95% in the last sub-period. The sub-period results for S&P 500 group are somewhat different from those of the Dow Jones and NASDAQ data sets. In the first sub-period the spot market leads in terms of price discovery for 45.83% of the periods although, after 2006 this lead position quickly fades and in the post-crisis period falls to 8.33%.

The choice of instruments (Nasdaq, Dow and SPX) of our paper has similarity to Chou & Chuang (2006) and Ivanov et al. (2013) and some of the results also echoed one another. However, Chou and Chuang (2006) conducted the analysis over a much shorter period of intra-day data from October 2000 to April 2001 and found that ETFs lead price discovery ONLY after ETFs are quoted using decimal instead of the fraction method. In contrast, Ivanov et al. (2013) used two methods: IS and PT, to study indices, index futures and index ETFs across the DJIA, S&P 500, S&P 400, NASDAQ 100 and Russell 2000 from January 2000 to December 2012 but ONLY at the daily level. They draw similar conclusion that the introduction of ETFs weakens the dominance of the index futures in revealing the underlying price updating process.

Further, none of the above studies or any other in the literature has ever observed the increased significance of spot markets in price discovery in recent periods. We suggest this is likely driven by the need for ETFs to track the index so that more active trading of ETFs leads to more active trades in the underlying stocks and hence the index. But such effects possibly become more visible only if a long-time dataset is

examined.

4.2 Information Share Results

Before any calculation of the information share can properly begin, some diagnostic checking on the residual correlations needs to be performed. As noted by Hasbrouck (2003) and Baillie and Bollerslev (2002), high correlations among innovations eventually lead to wide upper and lower bounds because the calculation of the upper bound (that is defined as the largest IS value) has to include the correlation between innovations¹⁸. To check the degree of accuracy of information share calculations, the innovation correlations need to be calculated and assessed.

Table 5: Correlations of Innovations

Table 5 represents the residual correlations between the pairs among our sample series.

	Dow Jones					
	DIA (ETFs)	DJI (Spot)				
DIA (ETFs)	1					
DJI (Spot)	0.68747	1				
	NASDAQ					
	QQQ (ETFs)	NQc (Futures)	NDX (Spot)			
QQQ (ETFs)	1					
NQc (Futures)	0.021568	1				
NDX (Spot)	0.870069	0.000559	1			
	S&P					
	SPY (ETFs)	SPc (Futures)	SPX (Spot)	ESc (Futures)	IVV (ETFs)	
SPY (ETFs)	1					
SPc (Futures)	0.411703	1				
SPX (Spot)	0.864133	0.440633	1			
ESc (Futures)	0.415253	0.951606	0.441703	1		
IVV (ETFs)	0.265931	0.093374	0.240949	0.091187	1	

¹⁸ An upper bound is achieved by putting a price variable in the first equation of VECM. See Section 3.2 for discussions about the upper and lower bounds.

From Table 5, we can see that the residual correlations among the ten price series are considerably high, especially among the spot and ETFs where the correlations are close to 1 in all three groups¹⁹. Under such a circumstance, the gap between the upper and lower bound of the spot and ETFs are expected to be large, and this is reflected in our calculations of the information share that is summarized in Table 6. The estimated upper and lower bounds are far apart for most cases, indicating the instability of the model estimation even though the general results suggest futures contribute the least to price discovery. Component share results in Section 4.1 are supportive of this view but we further perform the weighted price contribution test as a validation to the component share and information share methods. The spot indices and ETFs share similar status in terms of price contribution - in the Dow Jones and NASDAQ groups the spot market has a slight lead in the price discovery process when compared to ETFs. The results for S&P show that the major contribution to price discovery is shared among the two ETFs and the spot market, with the IVV ETF having a slightly higher price discovery contribution of 33.37%. The S&P group though shows a lead for ETFs over the spot, in line with the component share results²⁰.

¹⁹ There is no uniform way of classifying the degree of correlation that would lead to a false result. However, according to Hasbrouck (2003) and Baillie and Bollerslev (2002), a correlation of 0.56 is high enough to cause misleading result. Hence, it would be safe to conclude that the correlation matrix in our analysis implies that the IS results were inaccurate.

²⁰ Discussion of whether these information share results are consistent with the weighted price contribution results is in Section 4.3.

Table 6: The Calculation of Information Share Using a VECM Formulation

Table 6 reports the calculations of Hasbrouck (1995) information share with error bounds.

	Upper Bound Dow Jones		Lower Bound Dow Jones		Midpoint Dow Jones	
Type	Spot	ETFs	Spot	ETFs	Spot	ETFs
RIC	DJI	DIA	DJI	DIA	DJI	DIA
Mean	92.67%	77.03%	22.97%	7.33%	57.82%	42.18%
Median	98.80%	79.25%	20.76%	1.20%	59.10%	40.90%
Max	100.00%	100.00%	99.12%	60.89%	99.56%	74.33%
Min	39.11%	0.88%	0.00%	0.00%	25.67%	0.44%
St. D.	0.1206	0.2067	0.2067	0.1206	0.1436	0.1436

	Upper Bound NASDAQ			Lower Bound NASDAQ			Midpoint NASDAQ		
Type	Spot	Futures	ETFs	Spot	Futures	ETFs	Spot	Futures	ETFs
RIC	NDX	NQc	QQQ	NDX	NQc	QQQ	NDX	NQc	QQQ
Mean	90.52%	16.11%	87.73%	6.36%	5.66%	3.61%	48.44%	8.39%	43.17%
Median	96.79%	8.81%	93.85%	3.62%	0.07%	1.23%	50.27%	2.52%	45.28%
Max	100.00%	98.74%	100.00%	54.30%	92.20%	57.86%	76.68%	93.76%	68.26%
Min	0.08%	0.00%	6.97%	0.00%	0.00%	0.00%	0.04%	0.00%	2.47%
St. D.	0.1875	0.2122	0.17621	0.0924	0.1667	0.0678	0.1149	0.1750	0.1037

	Upper Bound S&P					Lower Bound S&P					Midpoint S&P				
Type	Spot	Futures	ETFs	Futures	ETFs	Spot	Futures	ETFs	Futures	ETFs	Spot	Futures	ETFs	Futures	ETFs
RIC	SPX	SPc	SPY	ESc	IVV	SPX	SPc	SPY	ESc	IVV	SPX	SPc	SPY	ESc	IVV
Mean	85.63%	11.03%	76.01%	11.96%	65.47%	15.12%	0.15%	2.46%	0.58%	1.27%	29.68%	2.93%	30.48%	3.54%	33.37%
Median	91.98%	4.23%	81.38%	4.43%	78.62%	10.53%	0.00%	0.42%	0.01%	0.14%	24.14%	0.67%	30.61%	0.88%	39.75%
Max	100.00%	95.81%	99.77%	98.60%	98.98%	69.87%	3.99%	43.13%	16.62%	22.03%	82.14%	38.44%	65.69%	42.47%	56.87%
Min	7.08%	0.00%	0.57%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%	1.47%	0.01%	0.16%	0.00%	0.03%
St. D.	0.1701	0.1669	0.2013	0.1793	0.2920	0.1609	0.0050	0.0532	0.0208	0.0306	0.1970	0.0600	0.0947	0.0741	0.1505

Tse et al. (2006) studied both intraday quotes and trades for the period May to July in 2004 on 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 the (electronically traded) futures contribute most to price discovery, followed by ETFs and then indices, (with little or no contribution from floor-traded futures). This is opposite to our findings that SPDR ETFs dominates the price discovery over both electronically and floor-traded futures and DIMOND controls the price discovery over Dow E-mini and its floor-traded futures. Kurov and Lasser (2004), which examined price discovery between the S&P 500 futures and S&P 500 E-mini as well as the NASDAQ 100 futures and NASDAQ E-mini. They apply the Hasbrouck (1995) information share method over a 12-month data period in 2000 and found both E-mini contracts lead price discovery. But no effects of ETFs were examined in their studies.

Although our study also involves floor-based trading and electronic trading of the DJIA ETF (similar to Tse et al., 2006), we instead find ETFs are now the dominant vehicle for price discovery across all of the main US price indices and that futures contracts play an insignificant role in price discovery. Such a major difference in the test results between Tse et al. (2006), Kurov and Lasser (2004) and our paper is, again, due to the fact that our data is based on much more extensive time period (across 11 years) than Tse et al. (2006) (from May to July in 2004, 2 months) and Kurov and Lasser (2004) (year 2000, 12 months).

4.3 Weighted Price Contribution Results

To provide further insights into the price discovery process over a day we use the weighted price contribution (WPC) method introduced by Barclay and Hendershott (2008), a measure to discover intraday price contributions of the same asset. The WPC results are calculated for every half an hour in a day and reported as both a monthly average and an average of the whole sample period. Table 7 summarizes the average WPC results every half an hour over each day across the sample period. In general, we find that before 12:00 in the morning the contributions to price discovery

mainly come from the ETF and spot markets while after midday, the price contributions come mostly from the futures market - the result holds for all of the three data sets. This means that the ETF markets are generally adjusting their prices earlier than the spot and futures markets as we found in the component share results.

Table 7: Weighted Price Contribution (WPC) Results

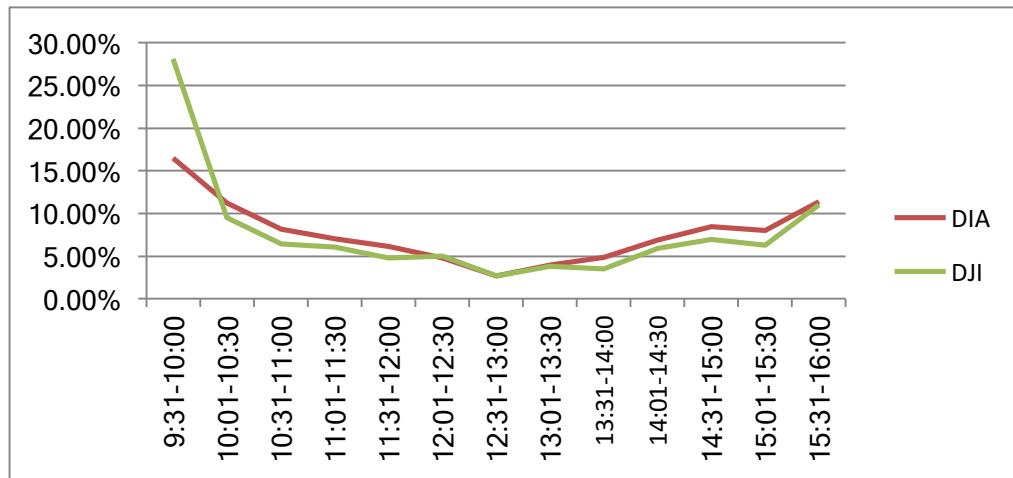
Table 7 summarizes the average WPC (Barclay & Hendershott, 2008) results every half an hour over each day of the sample period. The numbers specified in bold and italic type indicate that the market leads the period. In general, ETF and spot markets tend to lead price discovery in the morning and the futures take over the ownership after the mid-day. This suggests that the ETF markets are generally adjusting their prices earlier than the spot and futures markets.

Type RIC	Dow Jones		NASDAQ			S&P				
	ETFs	Spot	ETFs	Futures	Spot	ETFs	Futures	Spot	Futures	ETFs
	DIA	DJI	QQQ	NQc	NDX	SPY	SPc	SPX	ESc	IVV
9:31-10:00	16.46%	28.15%	18.64%	1.57%	17.58%	14.73%	1.89%	24.67%	2.29%	15.63%
10:01-10:30	11.21%	9.51%	12.81%	1.84%	12.15%	10.55%	2.47%	8.70%	2.74%	10.64%
10:31-11:00	8.14%	6.40%	9.04%	1.30%	8.45%	7.73%	1.62%	6.25%	2.14%	7.37%
11:01-11:30	7.03%	6.06%	7.42%	2.53%	7.10%	6.71%	3.14%	6.61%	3.40%	6.81%
11:31-12:00	6.13%	4.75%	6.15%	1.64%	5.95%	6.19%	2.27%	5.07%	2.34%	5.90%
12:01-12:30	4.76%	5.03%	5.28%	3.35%	5.33%	5.38%	3.41%	4.96%	4.01%	4.61%
12:31-13:00	2.71%	2.68%	4.12%	2.90%	4.02%	2.99%	4.26%	3.26%	4.79%	3.06%
13:01-13:30	3.96%	3.77%	3.05%	5.00%	2.60%	4.53%	3.88%	3.79%	5.46%	4.16%
13:31-14:00	4.83%	3.51%	5.12%	17.01%	5.04%	4.59%	14.41%	3.87%	15.31%	3.96%
14:01-14:30	6.89%	5.87%	6.33%	14.14%	6.65%	7.15%	11.90%	5.94%	13.12%	6.99%
14:31-15:00	8.48%	6.96%	6.97%	17.75%	6.85%	8.56%	15.88%	7.57%	16.19%	8.42%
15:01-15:30	8.04%	6.31%	6.19%	18.18%	6.82%	8.34%	14.30%	7.02%	15.83%	8.18%
15:31-16:00	11.37%	11.00%	8.90%	12.79%	10.55%	12.55%	20.56%	12.29%	12.39%	14.26%

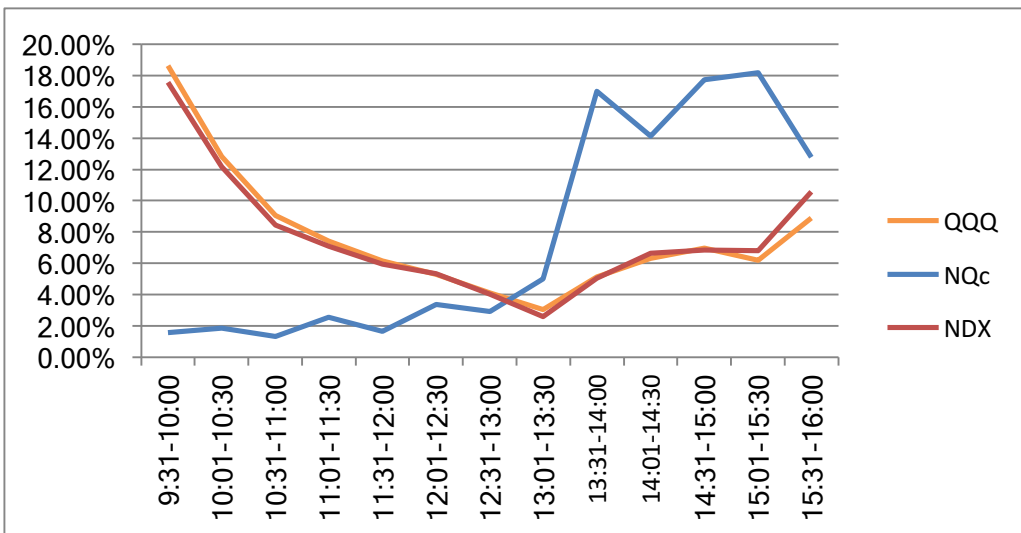
Figure 1 is a graphical representation of the results in Table 7. In the early part of the day, the ETFs and spot markets are leading the price discovery processes, with the ETFs usually slightly greater than spot market except for the first hour in the Dow Jones (first picture) and S&P (third picture) data sets.

Figure 1: Weighted Price Contribution (WPC) Results

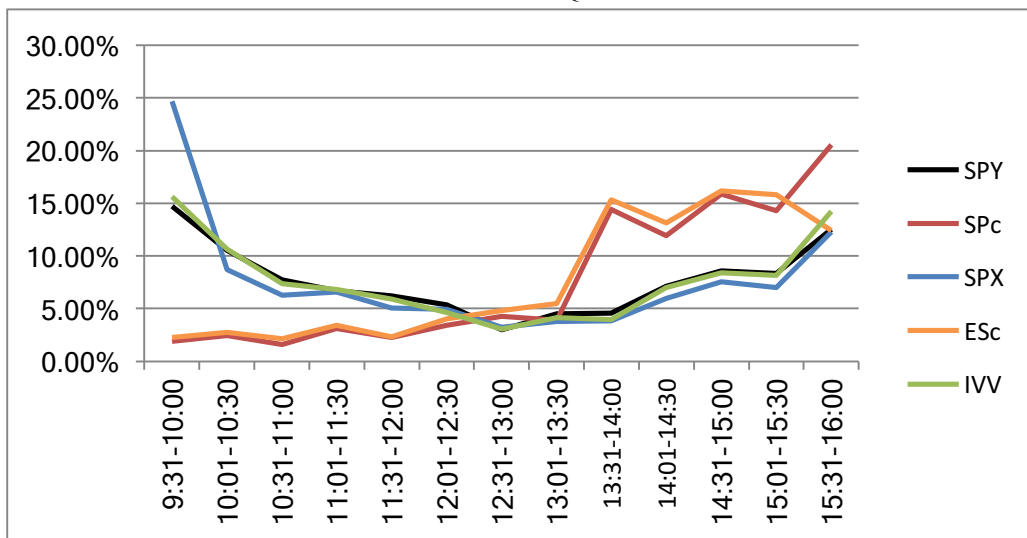
Figure 1 gives the graphical representation of the WPC results presented in Table 7. It provides the visualized change of the price discovery leading role of different series.



Dow Jones



NASDAQ



S&P

Following Table 7, in the Dow Jones data set, during the first hour the spot market has a price contribution of 28.15%, nearly one-third of the total price changes of the day occurred during this period of time. The ETF market also has the highest price contribution (for ETFs over the day) in the first half an hour in a day but only to a 16.46% of the total price changes of the day. After the first hour, except for 12:01pm to 12:30pm, the ETF markets all present a slightly higher level of price contribution. In the NASDAQ data set, up to 13:00pm the ETF market shows a higher price contribution which suggests that the ETF market adjusts to prices faster in the early part of the day. The spot market has a very close but slightly lower WPC result in comparison to the ETF market, and the futures market only starts to yield high price contributions after 13:00pm. Hence, the NASDAQ data set suggests that the ETF market leads the overall price changes followed by the spot market. The futures market responds in the slowest speed to price changes among the three markets which is consistent with the PT results. In the S&P 500 data set, we find similar results to the Dow Jones data set but with very high price contributions from the spot market in the first half an hour with a WPC of 24.67%. After this period, the two ETF markets mainly drive price movements until 12:30pm when the two futures markets begin to generate higher price contributions than the spot and ETF markets.

As the WPC method is designed to reveal intraday price evolutions of the same asset, in determining the effects of price discovery among markets we should give more weight to the first period of a day. In the component share results reported in Section 4.1, we found the dominant market to be the ETF market, and so we expect a similar pattern from the weighted price contributions results, that is, during the first half an hour of a day the ETFs' price contribution should be higher than the spot and futures markets. However, we find that, except for the NASDAQ data set, the greatest contributions to price discovery are from the spot market (Table 7).

We now take a closer look at the first half-hour results but on a monthly basis to

reveal how many periods each market is leading and also whether there are any outliers (of extremely high or low values) that may impact upon the average value of WPC. These results are reported in Table 8. We are able to confirm that the estimated average values of weighted price contribution are in line with the number of leading periods and there are no exceptionally large gaps among WPC results for the same asset in every market. Barclay and Hendershott (2008) and Jiang et al. (2012) suggest the ETF market may show more price contribution before the market opening time at 9:30am. This could possibly be the reason why the spot markets in the Dow Jones and S&P 500 groups have the highest price contribution in the first half hour as they adjust to movements in ETF prices. Nevertheless, due to the restrictions that we face in the availability of the data we could not further confirm this in our study. However, the weighted price contribution results support our earlier finding that futures markets play an insignificant role in price discovery whilst ETFs and spot markets do play an important informational role in the US market.

Table 8: WPC Results with the Number of Leading Periods of All Series

Table 8 shows the estimated average values of weighted price contribution of each asset is in line with the number of leading period. N.O.L.P means the number of leading periods. The results show that there are no exceptionally large gaps among WPC results for the same asset in every market.

	Dow Jones		NASDAQ			S&P				
Type	ETFs	Spot	ETFs	Futures	Spot	ETFs	Futures	Spot	Futures	ETFs
RIC	DIA	DJI	QQQ	NQc	NDX	SPY	SPc	SPX	ESc	IVV
Mean	16.46%	28.15%	18.64%	1.57%	17.58%	14.73%	1.89%	24.67%	2.29%	15.63%
Max	58.51%	73.12%	61.64%	16.98%	60.48%	50.59%	14.51%	64.20%	15.49%	88.36%
Min	-9.78%	-2.17%	-17.72%	-9.99%	-13.83%	-2.78%	-18.53%	-2.39%	-8.92%	-2.96%
N.O.L.P	17	115	64	6	38	10	0	109	0	13

5 Conclusion

Through the application of three different measures of price discovery to the three major US stock exchange indices (considering spot, futures and ETF markets), we examined the question of which market leads price discovery and whether this

contribution is the same for different indices and whether it has changed over time. The early literature in this area suggested that futures tended to lead the spot market (e.g. Hasbrouck, 2003). Some recent studies such as Chou & Chuang (2006) have suggested that ETFs have taken over the price discovery role from futures although some studies still found a leading role for futures. Our findings support the view that ETFs are now the dominant vehicle for price discovery across all of the main US price indices and that futures contracts play an insignificant role in price discovery. In addition, we find that spot markets have increased their importance as markets for price discovery. This, we suggest, is likely to be a consequence of ETFs being mostly created from physical replication of the spot index in the US.

The WPC results with half hour intervals also support the hypothesis that futures markets have lost their price discovery role to ETFs in relation to the major US stock market indices. However, the WPC results for the Dow Jones and S&P 500 markets suggest that the spot markets actually reflect market information more quickly. Some studies have suggested that ETFs adjust to price changes ahead of the spot market and those major price adjustments occur before the market opening time. Nevertheless, we could not confirm this in this paper due to the lack of pre-opening time data.

The evidence presented in this paper supports the view that ETFs play a dominant role in terms of price discovery in US stock markets. Given the volume of trading in ETFs this is not a surprising result. However, as index ETFs are generally physically replicated in the US the need to keep the ETF replicated induces changes in the prices of underlying constituents. As the underlying security may not be as liquid as the ETF itself, there are risks of mismatches and forced sales. The dominance of index ETF trading has raised therefore raised questions about the distortions this can create in the valuation of the underlying assets and of potential systemic risk. In addition, there are concerns that growth in short term traders in index ETFs can increase the volatility of the prices of the underlying stocks in the index. This has led to calls for the SEC to consider curtailing the growth of ETFs. Any consideration of curtailing the growth of

ETFs should consider the implications for price discovery in the market.

ETFs trading, like other actively traded instruments, has great impact on both investors and regulators. On the other hand, various market participants' mind sets and attitudes towards different issuances, especially the fundamentally related ones would also influence price movements. For example, back to Fukushima nuclear disaster in 2011, whilst the home market in Tokyo was closed the Japanese ETFs listed in the U.S. continued to trade. These largely eased investors adjust their investment portfolios according to changes about the radioactive leaks from the power generator. No doubt ETFs maintain excellent price discovery functions that enable economic agents to make their investment decisions effectively and efficiently. Over the past few years, the asset attracts massive long-term as well as short-term investors. Empirical evidence shows ETFs attract more short-term investors than long-term ones. Consequently, the extra liquidity coming from ETFs due to short-term trading when the market is booming may be illusory if the financial market is depressed, as the short-term traders will leave the market. In this respect, ETFs are double-edged sword -- they can increase the volatility of the pricing of the stocks they own, and meanwhile exacerbate the volatility of the financial market (due to short-term traders). This calls for the Securities and Exchange Commission (SEC) to consider curtailing the growth of ETFs, or to ensure the trading remains orderly, as the extra liquidity brought to the market by ETFs may cause issues of overall instability of the U.S. stock market. SEC is advised to examine the relation between ETFs share pricing and their underlying portfolio holdings and the impact on investors when these connections break down. The regulators are therefore urged to implement laws on financial services to improve investor protection standards.

However, we are aware that there are some limitations of this kind of studies. For example, it is widely acknowledged in the literature that the Hasbrouck (1995)'s information share method, due to the restrictions of the upper and lower bounds, causes biased results when the innovations of the price series are highly correlated

with each other. The Gonzalo and Granger (1995) permanent and transitory decomposition method, in contrast, is found to be more accurate in revealing the overall price discovery in such a situation. Since the use of the information share or the permanent and transitory decomposition method adopted by our analysis is not new, employing alternative methods to verify the various claims made in this paper is, therefore, needed. We, subsequently, chose a modified version of the Barclay and Hendershott (2008) method to provide a robustness check on the PT and IS results. Alternatively, one could consider the use of the Madhavan et al. (1997) structural model to determine the permanent impact of order flow innovation. They argued that a comparison of the adverse selection parameter and the order processing cost parameter can serve as a useful validation to the PT method. Lien and Shrestha (2009) also attempted to address the bias in the Hasbrouck (1995) method and proposed a modified IS measure (MIS) that is free from the requirements of upper and lower bounds. They decomposed the error covariance matrix into a standard deviation diagonal matrix and an eigenvector so that factorization can be achieved to eliminate the excessive upper and lower bounds. The use of these alternative approaches/modifications may help to improve measurement of price discovery.

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