

Exchange-traded funds, liquidity and volatility

Timothy Krause, Sina Ehsani & Donald Lien

To cite this article: Timothy Krause, Sina Ehsani & Donald Lien (2014) Exchange-traded funds, liquidity and volatility, *Applied Financial Economics*, 24:24, 1617-1630, DOI: [10.1080/09603107.2014.941530](https://doi.org/10.1080/09603107.2014.941530)

To link to this article: <https://doi.org/10.1080/09603107.2014.941530>



Published online: 25 Jul 2014.



Submit your article to this journal [↗](#)



Article views: 3099



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 21 View citing articles [↗](#)

Exchange-traded funds, liquidity and volatility

Timothy Krause^{a,*}, Sina Ehsani^b and Donald Lien^b

^a*Sam and Irene Black School of Business, Penn State Erie – The Behrend College, Erie PA 16563, USA*

^b*College of Business, University of Texas at San Antonio, San Antonio, TX 78249, USA*

Given the exponential growth in exchange-traded fund (ETF) trading, ETFs have become a significant factor in the volatility generating process of their largest component stocks. A simple model of trading is developed for securities that are included in ETFs, and empirical support is provided for the model hypotheses. Volatility spillovers from ETFs to their largest component stocks are economically significant. These spillovers are increasing in liquidity, the proportion of each stock held by the fund, deviations from net asset value, ETF flow of funds and ETF market capitalization. The results are consistent with a positive volume–volatility relation and trading-based explanations of volatility, and are generally stronger for smaller stocks.

Keywords: exchange-traded fund; ETF; volatility spillover; liquidity; volume

JEL Classification: G12; G14

I. Introduction

Over the past decade, exchange-traded funds (ETFs) have become the investment vehicle of choice for investors and traders seeking rapid, low-cost exposure to broad equity market indices, industry sectors and other asset classes. Hedge fund managers, institutional investors and individuals increasingly turn to ETFs to implement their investment strategies. Thus, trading in these securities has become an important source of information dissemination in US equity markets. This study examines how volatility information flows among nine large sector ETFs and their largest component stocks. In the light of the exponential growth in these securities, regulators and market observers have raised concerns that ETFs may be related to stock market volatility (see, for example, CFTC-SEC (2010a, b) and Bradley and Litan (2010)). We demonstrate that volatility spillovers among popular industry ETFs and their largest component stocks are

economically significant and important to their volatility-generating processes. Additionally, we identify several sources of volatility spillovers that are positively related to ETF trading activity. These include the liquidity of the ETFs and their largest component stocks, the proportion of each stock in its respective ETF, flow of funds, deviations from net asset value (NAV) and the size of the industry ETF. These factors are significant due to the nature of ETF trading and the high levels of arbitrage involved in the creation/redemption process. We estimate volatility spillovers using the recently developed model of Diebold and Yilmaz (2009, 2012) and demonstrate that spillovers are driven by these factors. The results are consistent with a positive volume–volatility relation and trading-based explanations of volatility. The study follows in the long stream of the literature that examines the efficient markets hypothesis. In theory, ETF prices and volatility should be largely determined by movements in each of its component stocks. Lead–lag

*Corresponding author. E-mail: tak25@psu.edu

relationships in volatility and price discovery may flow from the underlying securities to ETFs since ETFs are composed of these securities, and information transmission is not necessarily instantaneous. But this type of causality should not flow in the opposite direction as stock prices should be only indirectly influenced by the price of a market-based or industry-based ETF (perhaps due to new market-wide or industry-wide information). However, the results documented here indicate that trading in ETFs contributes to the future volatility innovation processes of their underlying securities. Thus, we extend the literature on volatility spillovers and their causes, in support of research and press reports that trading of ETFs is related to stock market volatility.

Because large institutions and traders are able to exchange ETFs for an equivalent portfolio of stocks and vice versa, they provide ideal opportunities for arbitrage.¹ Whenever an ETF share price becomes more (less) expensive than the value of the underlying portfolio, the arbitrageur can buy (short) the underlying stocks, create (redeem) ETF shares and short (buy) the ETF on the market. These positions offset and the arbitrageur does not face any financial risk to remove the mispricing and he continues trading until prices reflect fundamental values. While the creation/redemption process occurs after market hours as authorized participants (APs) create or redeem ETF shares from existing inventories, the inventory management process takes place during market hours. Also, arbitrageurs that are not APs may also attempt to arbitrage deviations from NAV through the use of ‘tracking baskets’. Any shock to the ETF price, whether created by new fundamental information or simply by liquidity traders taking advantage of ETF market depth, should be eliminated quickly with a correction in the price of ETF, the underlying stocks or both.

Recent research has focused on ETFs due to their growth and popularity. Da and Shive (2013, p. 6) find that the arbitrage activity involved in ETF trading ‘propagates non-fundamental shocks from the ETFs to a broad cross-section of stocks they hold’, and that ETF turnover is closely related to co-movement in component stocks. Bae *et al.* (2012) find that ETFs negatively affect firm value and increase systematic risk while positively influencing liquidity, especially for small stocks. Madura and Ngo (2008), however, find positive valuation effects on the largest 10 stocks in ETFs subsequent to their inclusion in the funds, especially within relatively large ETFs. Clifford *et al.* (2014, forthcoming) find that ETF flows are driven by ETF volume, bid–ask spreads and deviations

from NAV, consistent with ‘return chasing’ that is found in the literature on mutual funds.

Financial theory and the law of one price tell us that the prices of instruments such as ETFs should be priced in a manner that is dependent on the value of their underlying securities. However, substantial research documents the fact that derivative prices often lead spot prices (see, for example, Chan, 1992; Hasbrouck, 2003; Roll *et al.*, 2010; and Johnson and So, 2012). Although ETFs are not technically derivatives since they are composed of actual securities and are securities themselves since they represent a claim on the cash flows of their underlying securities, they ‘derive’ their value from other instruments. Several studies document the fact that ETFs add additional information to stock price discovery (see, for example, Hasbrouck, 2003; Hegde and McDermott, 2004; Madhavan, 2011), but the present study revolves around the volatility generating process in component stock prices. The results here are more closely related to those of Ben-David *et al.* (2014, p. 33), who find that ‘arbitrage activity between ETFs and the underlying securities leads to an increase in stock volatility’. While the underlying intuition of their paper is quite similar to this article, they employ alternative empirical techniques and as well as high-frequency data. As is the case in the present study, they also find evidence of price shocks in component stocks that stem from ETF trading activity. They use ETF aggregate stock ownership data to make the claim that ETF trading directly increases component stock volatility. Our study is based on a theoretical model of trading in these securities that is supported by empirical evidence of volatility spillovers from ETFs to their largest component stocks. We document significant lead–lag effects on volatility that persist over longer than daily timeframes. Additionally, we provide evidence regarding the sources of these spillovers that occur through trading and arbitrage activity and are also related to fund characteristics.

Given that trading in ETFs may affect future returns and volatility of their underlying stocks, we also examine the liquidity characteristics of these securities and their relation to volatility spillovers. The theoretical relation between the intensity of information transmission and volatility is prominent in Kyle (1985) and Admati and Pfleiderer (1988). In both models, higher trading volumes increase the presence of informed traders such that the price impact of volume (λ) is attenuated. De Long *et al.* (1990) and Shleifer and Vishny (1997) develop models whereby noise traders contribute to price volatility. Avramov *et al.* (2006) and Malinova and Park (2010) propose theoretical models of trading where higher

¹ This is accomplished via the mechanism of ‘creation’ and ‘redemption’ units at large institutions that are designated ‘authorized participants’ (APs).

trading volumes induce excess volatility. Empirical evidence regarding the relationship between liquidity and volatility is provided by Bessembinder and Seguin (1992), Jones *et al.* (1994) and Chan and Fong (2000).²

In addition to the theoretical and empirical examinations of liquidity and volatility, the study is motivated by the dramatic increase in the popularity of ETFs over the past decade, both in terms of assets under management and trading volumes. According to BlackRock, Inc., one of the world's largest asset managers and ETF issuers, US ETF assets passed the \$1 trillion mark on 16 December 2010 (Blackrock, Inc., 2010). In terms of trading volume, US ETFs in June 2011 accounted for 26% of all US equity dollar volume, up slightly from 22% of turnover in December 2010, but down from the peak of 43% in November 2008 (Blackrock, Inc., 2011). In addition to the exponential growth of ETFs as investment vehicles, the use of this particular data is motivated by the some observers who deem them a source of market instability. Bradley and Litan (2010, p. 2) conduct an in-depth study of ETFs and conclude that they pose 'unquantifiable but very real systemic risks of the kind that were manifested very briefly during the "Flash Crash" of 6 May 2010'. The joint SEC-CFTC report 'Findings Regarding the Market Events of 6 May 2010' (CFTC-SEC, 2010a, p. 39) notes that 'equity-based ETFs were disproportionately affected by the extreme price volatilities of that afternoon'. In summary, there appears to be substantial empirical and anecdotal evidence of a link between ETF liquidity and stock market volatility, and the remainder of this article explores this relation.

II. Motivation

The main goal of this study is to test whether volatility flows from ETFs to their largest underlying stocks, and if so, what determines the size of these spillovers. A simple model of trading is proposed to identify potential drivers of volatility spillovers for stocks that are included in ETFs. In the linear pricing framework of Kyle (1985), the price of a stock at any point in time depends on the available information, order flow and a coefficient representing the market depth of the stock: $\tilde{P}_i^t = \tilde{\delta}_i^t + \lambda_i(\tilde{\omega}_i^t)$, where $\tilde{\delta}_i^t$ is the available information for stock i at time t , λ_i is price impact measure (illiquidity) for stock i , and $\tilde{\omega}_i^t$ is the order flow. The price of an ETF should be equal to a weighted average of the underlying stocks: $\tilde{P}_{ETF}^t = \sum_{i=1}^n a_i \tilde{P}_i^t$, where a_i is the proportion of stock i in ETF's portfolio and \tilde{P}_i^t is the corresponding component stock price. Large

traders are able to exchange ETFs for an equivalent portfolios of stocks, thus if for any reason the ETF price deviates from its fundamental value, arbitrageurs are able to exchange units of the ETF for underlying stocks and realize an arbitrage profit without facing any financial risk. Whenever a unit price becomes more (less) expensive than the value of the underlying portfolio, the arbitrageur can buy (short) the underlying stocks, create (redeem) a unit and short (buy) the ETF on the market. The trader can continue trading and realize profits until prices reflect fundamental values, thus any shock to the ETF price should be eliminated quickly with a correction in the price of ETF, the underlying stocks or both. The ETF's price deviation from its fundamental value is assumed to be normally distributed ($\tilde{\varepsilon} \sim (0, \sigma_\varepsilon^2)$).

When a shock ε is realized, price of the ETF will be:

$$P_{ETF} = \sum_{i=1}^n a_i P_i + \varepsilon \quad (1)$$

Assuming that arbitrageurs trade in both the ETF and the underlying securities until the mispricing is removed, we have:

$$P_{ETF} - \Delta P_{ETF} = \sum_{i=1}^n a_i (P_i + \Delta P_i) \quad (2)$$

Because the entire process occurs relatively quickly, information ($\tilde{\delta}_i^t$) is assumed to be constant. Consequently, replacing the linear pricing rule and (1) in (2) obtains:

$$\sum_{i=1}^n a_i \lambda_i \Delta \omega_i + \lambda_{ETF} \Delta \omega_{ETF} = \varepsilon \quad (3)$$

The arbitrageur takes no risk and is able to create and/or redeem the exact proportion of each underlying stock to remove the mispricing; as a result the order flow for each stock is proportional to the holding of that stock in the portfolio:

$$\frac{\Delta \omega_n}{\Delta \omega_1} = \frac{a_n}{a_1}, \dots, \frac{\Delta \omega_n}{\Delta \omega_{n-1}} = \frac{a_n}{a_{n-1}}, \frac{\Delta \omega_n}{\Delta \omega_{ETF}} = a_n \quad (4)$$

By substitution of (4) into (3) we solve for $\Delta \omega_{n_A}$ and the corresponding price change given the price shock $\tilde{\varepsilon}$ is:

$$E(\Delta \tilde{P}_i | \tilde{\varepsilon}) = \frac{a_i \lambda_i \tilde{\varepsilon}}{\sum_{j=1}^n a_j^2 \lambda_j + \lambda_{ETF}} \quad (5)$$

² Further evidence is provided by Chordia *et al.* (2002), French and Roll (1986), Haugen (2010) and Haugen *et al.* (1991).

The price process includes an additional source of volatility, and because the fundamental price process and the deviation shocks (supply/demand or liquidity shocks) are not correlated, each component stock's new variance will now be:

$$\tilde{\sigma}_{P_i}^2 = \sigma_{P_i}^2 + \left(\frac{a_i \lambda_i}{\sum_{j=1}^n a_j^2 \lambda_j + \lambda_{ETF}} \right)^2 \sigma_e^2 \quad (6)$$

The first term on the right-hand side of Equation 6 represents the stock's fundamental volatility, while the second term captures ETF to stock volatility spillover. The size of the spillover therefore depends on the illiquidity of the stock, the illiquidity of the ETF, the proportion of the stock in each ETF and the variance of the shock. In order to capture the second term, we use the Diebold and Yilmaz (2009, 2012) volatility spillover model to test our hypotheses in (6) by examining how these spillovers are related to liquidity, arbitrage and other factors related to trading in ETFs.

III. Data

The study utilizes daily ETF and component stock return and price data from 1 March 2003 to 31 December 2013, obtained from Bloomberg Professional®, for nine Select Sector SPDR ETFs. We use Bloomberg price data since it is published as of the 4:00 PM ET stock market close to make it consistent with the component stock data. These sector ETFs represent all of the sectors in the S&P 500,

thus all of the component stocks of these funds comprise the broad market index and roughly 80% of US market capitalization. The data include daily high, low and closing prices for each ETF as well as the 10 largest component stocks that comprise the holdings of each ETF. We obtain the proportions of each component stock in each ETF from the CRSP Mutual Fund Database. The proportion data are quarterly for the first two years and monthly thereafter. Following Madura and Ngo (2008), we choose to use only the top 10 stocks in each ETF to maintain tractability in the spillover model. On average, these 10 stocks comprise between 41.44% (XLF – Financials) and 66.72% (XLI – Industrials) of total ETF value, which is significantly more than many 'tracking baskets' used by non-APs to implement arbitrage strategies.

Daily NAV, total net assets and market capitalization data are also obtained from Bloomberg. There are 2729 observations for each of the ETFs and roughly the same amount for each of their respective component stocks. We present summary statistics for the returns of the ETFs and their largest component stocks in Table 1, where all returns are expressed in percentages. For each of the ETFs and their largest component stocks, we also collect daily dollar turnover, defined as trading share volume times price and calculated on an intraday basis by Bloomberg. We present average daily turnover for the ETFs (by year) in Table 2, where the massive growth of these securities over the past decade is evident, especially in the extremely popular Energy and Financials sectors.

Table 1. Summary statistics of daily returns for ETFs and 10 largest component stocks, 1 March 2003 to 31 December 2013

	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY	All
	Basic materials	Energy	Financials	Industrials	Technology	Consumer staples	Utilities	Health care	Consumer discretionary	Total/ Mean
Panel A: ETF returns										
N	2729	2729	2729	2729	2729	2722	2729	2729	2729	24 554
Mean	0.066	0.082	0.035	0.048	0.048	0.066	0.036	0.028	0.063	0.053
Median	0.053	0.092	0.000	0.035	0.035	0.052	0.044	0.000	0.027	0.037
SD	2.225	2.264	3.399	1.832	1.832	2.225	1.382	1.575	2.003	2.144
Min	-20.79	-26.71	-81.60	-17.92	-17.92	-20.79	-10.51	-28.31	-25.75	-81.60
Max	26.78	26.43	90.22	19.99	19.99	26.78	17.69	15.10	43.32	90.22
Panel B: component stock returns										
N	27 280	25 960	26 748	26 874	26 874	27 210	27 077	27 002	26 874	241 899
Mean	0.034	0.052	-0.001	0.035	0.032	0.031	0.027	0.028	0.039	0.031
Median	0.104	0.119	0.037	0.084	0.097	0.072	0.088	0.039	0.063	0.075
SD	1.617	1.855	2.180	1.377	1.341	0.855	1.130	1.032	1.406	1.471
Min	-13.25	-15.60	-18.23	-9.88	-9.05	-6.21	-7.73	-10.29	-12.36	-18.23
Max	13.15	15.25	15.19	10.17	13.01	6.66	11.40	11.38	9.33	15.25

Notes: Table 1 presents summary statistics of returns for nine Select Sector SPDR ETFs and their 10 largest component stocks for the sample period of 1 March 2003 to 31 December 2013. All returns are presented in percentages. Each of the 10 largest component stocks is identified using the CRSP Mutual Fund Database as of 31 December 2013.

Table 2. Industry ETF average daily share turnover (\$ millions)

	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLV
	Basic materials	Energy	Financials	Industrials	Technology	Consumer staples	Utilities	Health care	Consumer discretionary
Year									
2003	12	10	58	9	11	5	12	4	6
2004	28	65	97	19	13	11	21	13	11
2005	60	680	220	27	21	21	60	24	26
2006	112	1280	263	47	41	39	111	40	40
2007	259	1520	1430	152	69	58	239	69	101
2008	482	2460	3520	295	150	120	234	134	193
2009	265	1230	1730	258	144	137	197	162	168
2010	383	1040	1450	484	256	184	206	231	260
2011	512	1510	1300	712	312	275	264	343	317
2012	312	918	977	499	265	208	255	218	265
2013	257	847	865	434	236	345	389	330	308
Mean	244	1051	1083	267	138	128	181	143	154
CAG (%)	36.3	55.7	30.9	48.1	35.9	54.0	41.8	54.8	48.4

Notes: Table 2 presents average daily dollar turnover, by year, for the nine industry ETFs during the sample period of 1 March 2003 to 31 December 2013. The data are calculated as price times volume on an intraday basis by the Bloomberg Professional® service, and is presented in millions of US dollars. CAG, compound annual growth.

IV. Methodology and Results

The generalized volatility spillover model

The natural setting in which to examine the relationship among the volatilities of ETFs and their component stocks is the literature on volatility spillovers. Much of this research applies GARCH models to focus on the effects of negative returns, interdependence and volatility ‘contagion’ (see, for example, Forbes and Rigobon, 2002; Hamao *et al.*, 1990; Lin *et al.*, 1994). These studies and many others provide significant evidence of volatility spillovers across countries, asset classes and securities. But the objective here is to model the spillovers among relatively large numbers of securities simultaneously over time, so we use the recently developed spillover model of Diebold and Yilmaz (2009, 2012; hereafter DY). This methodology provides an efficient and tractable estimation procedure that calculates rolling average variance decompositions to generate time series’ of volatility spillovers. The approach is similar to the nonlinear multiplicative error models developed by Engle (2002) and Engle *et al.* (2012).

In order to examine volatility spillovers among these ETFs and their largest component stocks, we use the model of Diebold and Yilmaz (2009, 2012), which relies on variance decompositions. The advantage of the DY approach is that it enables us to generate time series’ of spillover levels. We utilize these time series’ to link volatility spillovers to measures of liquidity over the past decade. The original spillover model in Diebold and Yilmaz (2009) relies on Cholesky factorization to achieve orthogonality, making it sensitive to the ordering of

variables. The authors compensate for this limitation by rotating and randomizing orderings to achieve robust results. In their 2012 paper, however, DY adopt the generalized VAR framework of Koop *et al.* (1996) and Pesaran and Shin (1998), hereafter KPPS, which results in a model that is not sensitive to the ordering of variables. The more recent model specification is used here to avoid the ordering of variables issue.

For each ETF and their 10 largest component stock returns, 11-variable VARs (VAR(p)) are estimated using p equal to five lags to represent one week of trading activity:

$$x_t = \sum_{i=1}^5 \phi_i x_{t-i} + \varepsilon_t, \text{ where } \varepsilon \sim (0, \Sigma), i.i.d. \quad (7)$$

Using a moving average representation, this expression becomes:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (8)$$

where

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \dots + \phi_5 A_{i-5} \quad (9)$$

where in A_0 is an 11×11 identity matrix, where $A_i = 0$ for $i < 0$, and the moving average coefficients are used to construct variance decompositions. Thus the fraction of the H -step-ahead error variance in a forecast of x_t is calculated as shocks to $x_j \forall j \neq i$ for each i . In these

estimations $H = 10$ in order to generate 10-day ahead forecasts from the variance decompositions. DY define *own variances shares* as ‘the fractions of the H -step-ahead error variances in forecasting x_i that are due to shocks to x_i for $i = 1, 2, \dots, N$, and *cross variance shares*, or spillovers, as the fractions of the H -step-ahead error variances in forecasting x_i that are due to shocks to x_j , for $i, j = 1, 2, \dots, N$, such that $i \neq j$ ’ (p. 58). Thus each firm’s H -step-ahead variance decomposition is denoted by $\theta_{ij}^g(H)$ for $H = 1, 2, \dots$:

$$\theta_{ij}^g(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)} \quad (10)$$

The variance matrix for the error vector ε is denoted by Σ , and the SD of the error term for the j th equation is σ_{jj} . The selection vector e_i contains one as its i th element and zeros otherwise. Because the generalized variance decomposition framework of KPPS does not orthogonalize the innovations from the error term, the contributions to the variance of the forecast error may not sum to unity. Thus DY ‘normalize’ each entry in the decomposition matrix (*own* and *cross* variance shares) by the row sum as follows:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (11)$$

By definition, therefore, $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

DY also construct the *total volatility spillover index* using the volatility contributions from the preceding variance decomposition:

$$\begin{aligned} S^g(H) &= \frac{\sum_{i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 \\ &= \frac{\sum_{i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100 \end{aligned} \quad (12)$$

As DY observe in their 2012 paper, this ‘is the KPPS analog of the Cholesky factor based measure used by Diebold and Yilmaz (2009, p. 59)’ in which they measure global equity spillovers. They note that the index measures ‘the contribution of spillovers of volatility shocks ... to the total forecast error variance’ (p. 59). The present study focuses on the individual directional spillover contributions (*cross variance shares*) from the ETFs to their component stocks and also in the reverse direction.

Volatility spillover analysis

The DY framework is used to analyse volatility spillovers among nine popular ETFs and their 10 largest component stocks. To do this, daily estimates of price variance are required. We estimate the daily variance of each security using:

$$\hat{\sigma}_{it}^2 = 0.361 \left(\ln(P_{i,t}^{high}) - \ln(P_{i,t}^{low}) \right)^2 \quad (13)$$

where P_{it}^{high} is the maximum (high) price observed for stock or ETF i on day t , and P_{it}^{low} is the minimum (low) price observation. Support for this measure of price variance is provided by Parkinson (1980), Alizadeh *et al.* (2002) and Chan and Lien (2003), since the measure is quite sensitive to variations in dispersion. In Table 3 summary statistics are provided for this calculation on an annualized percentage basis such that $\hat{\sigma}_{it} = 100 \sqrt{255 \cdot \hat{\sigma}_{it}^2}$. While the mean values for annualized SD are generally in the 20–30% range for these high capitalization companies, there are clearly some extreme values observed during the financial crisis.

Utilizing the methodology outlined above, *total volatility spillover indexes* are calculated for each of the ETFs and their respective component stocks. We utilize a 200-day rolling estimation period, five lags in the VARs and a 10-day forecast horizon, and then plot the total volatility spillover indexes and a moving average of ETF turnover (data from Table 2) in Fig. 1. Each of the spillover plots is characterized by the same periodic volatility ‘bursts’ observed in Diebold and Yilmaz (2009), who study global equity spillovers up to 2007. These spikes in volatility are clearly seen during the financial crisis in 2007 and surrounding the European debt crisis of 2011. In general, the volume plots reach peaks and troughs prior to the volatility spillovers, so it seems that increases in trading volumes precede spikes in volatility spillovers. The overall increasing levels of total spillovers are also consistent with rising levels of arbitrage activity in ETFs and their component stocks up until about 2011 when overall ETF volume peaks and begins to decline. Additionally, while there was no observable trend in the spillover plots in Diebold and Yilmaz (2009) (their sample is from the period 1992 to 2007), the plots in Fig. 1 display clear upward trends since 2003, when spillovers were at relatively low levels. The inception of this trend coincides with the exponential growth in the trading volumes of the ETFs from the period 2003 to 2011 that can be seen in Table 2. This result provides the first indication of the volume–volatility relation among ETFs and their component stocks. The concurrent upward trends in volume and volatility are consistent with the trading-based explanations of volatility noted by Chan (1992), Chordia *et al.* (2002) and Haugen (2010).

While the prior analysis is useful to examine the behaviour of total volatility spillovers among all these securities,

Table 3. Summary statistics of annualized volatility for ETFs and 10 largest component stocks (annualized percentages)

	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLV	All
	Basic materials	Energy	Financials	Industrials	Technology	Consumer staples	Utilities	Health care	Consumer discretionary	Total/Mean
Panel A: ETF volatilities										
N	2729	2729	2729	2729	2729	2722	2729	2729	2729	24 554
Mean	17.958	20.028	19.379	15.288	15.122	10.679	14.240	12.367	15.400	15.608
Median	14.563	16.641	13.326	12.356	12.509	8.732	11.757	10.053	11.840	12.178
SD	12.567	14.290	19.019	10.967	10.577	8.272	10.478	9.305	12.639	12.722
Min	3.04	3.91	2.42	2.77	2.66	2.43	3.59	2.09	2.82	2.09
Max	118.79	170.15	169.23	111.27	140.66	110.10	148.75	122.65	143.33	170.15
Panel B: component stock volatilities										
N	27 125	25 969	23 389	23 990	23 990	27 125	25 302	25 551	25 327	227 768
Mean	25.088	26.004	28.433	21.298	21.297	25.093	17.014	19.112	23.381	22.981
Median	20.311	21.364	19.149	18.122	18.120	20.312	14.022	16.170	19.309	18.416
SD	17.682	18.656	33.924	13.041	13.042	17.683	11.960	12.229	15.878	18.446
Min	0.61	0.00	2.41	2.95	2.95	0.61	0.69	2.89	0.00	0.00
Max	245.13	510.31	1375.07	248.85	248.85	245.13	220.50	204.94	371.81	1375.07

Notes: Table 3 presents summary statistics for our volatility estimates for the nine ETFs and their 10 largest component stocks for the sample period of 1 March 2003 to 31 December 2013. Daily volatility is estimated using daily high and low prices using the method suggested by Parkinson (1980) and others. For each ETF and stock i , on day t , we calculate:

$$\hat{\sigma}_{it}^2 = 0.361 \left[\ln(P_{i,t}^{high}) - \ln(P_{i,t}^{low}) \right]^2$$

where P_{it}^{high} is the maximum (high) price observed for stock or ETF i on day t , and P_{it}^{low} is the minimum (low) price observation. We provide summary statistics for this calculation on an annualized percentage basis such that $\hat{\sigma}_{it} = 100 \sqrt{255 \cdot \hat{\sigma}_{it}^2}$.

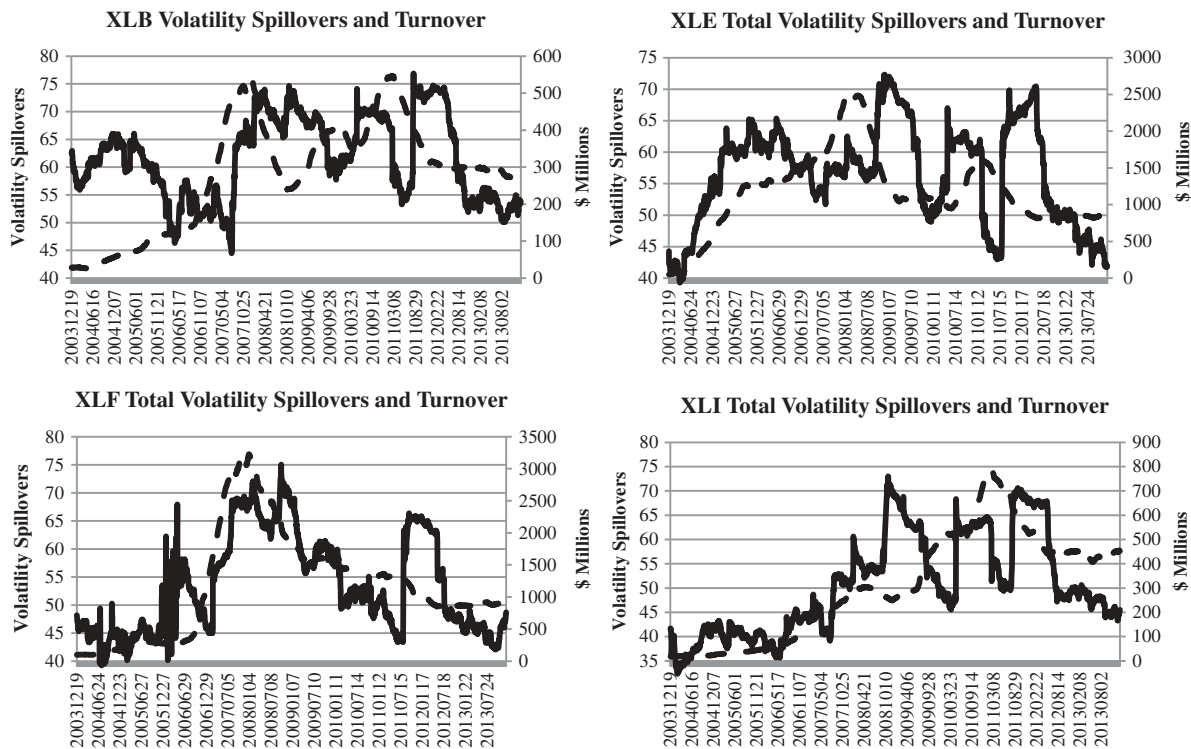


Fig. 1. This figure shows the *total volatility spillover indexes* for each of the ETFs and their respective component stocks, as in Diebold and Yilmaz (2012). The time series estimates are presented here using a 200-day rolling estimation period, five lags in the VARs and a 10-day forecast horizon. Each of the spillover plots is characterized by the same periodic volatility ‘bursts’ observed in Diebold and Yilmaz (2009), who study global equity spillovers up to 2007. These spikes in volatility are clearly seen during the financial crisis in 2007 and the European Debt Crisis of 2011

Table 4. Directional volatility spillover table – ETF to component stock spillovers

Contribution from										
	Symbol	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLV
To	ETF	23.0	18.5	21.1	22.2	26.9	71.4	19.8	27.8	27.5
	STK1	13.9	14.6	12.1	9.2	9.8	7.1	12.8	9.0	14.3
	STK2	15.5	11.3	13.3	13.2	12.1	19.0	10.8	12.7	15.2
	STK3	13.9	13.9	12.4	12.6	14.0	17.2	10.6	12.8	13.7
	STK4	13.8	12.8	13.3	14.2	13.8	25.5	7.6	13.2	15.6
	STK5	12.3	13.0	13.2	12.7	14.9	13.9	12.1	11.7	17.2
	STK6	11.6	12.7	8.7	13.4	14.4	22.9	12.0	11.3	17.0
	STK7	12.3	12.3	14.8	11.4	15.9	15.7	12.1	11.1	14.9
	STK8	12.2	9.0	13.8	13.3	12.9	20.0	11.2	12.1	11.2
	STK9	10.8	12.5	11.9	12.2	15.7	19.1	12.7	12.3	14.7
	STK10	12.2	5.4	7.9	12.0	12.6	16.4	11.9	11.2	15.9
	Contr. to others	128	118	121	124	136	177	114	117	150
	Contr. including own	151	136	142	146	163	248	133	145	177

Notes: Table 4 contains approximate directional volatility spillovers transmitted by ETF i (contained in the top row) to ETF or stock j (contained in the left-most columns). The ‘from’ spillovers are approximate since the generalized variance decompositions may not sum to one and they are normalized by row sum and not column sum, as in Diebold and Yilmaz (2012). The results are qualitatively similar when normalizing by column instead of by row. The component stocks are sorted such that the stock that comprises the greatest percentage of each ETF is just below the ETF in the left-most column, and then in descending order of proportion.

we are particularly interested in the interaction of volatility spillovers among the ETFs and their largest component stocks. DY provide a method to examine these relationships through the calculation of ‘directional’ volatility spillovers. They use the normalized forecast variance shares from Equation 11 to compute approximate directional volatility spillovers transmitted by an ETF or stock i to an ETF or stock j . These spillovers are approximate since the generalized variance decompositions may not sum to one, as noted above. DY normalize by row, so the directional spillovers ‘from others’ sum to unity across rows, but the spillovers ‘to others’ do not sum to one by columns. All of the spillover tests in this article are repeated using normalization by column instead of row, and the results are qualitatively similar. This methodology is applied to each of the nine sector ETFs and their 10 largest component stocks to compute directional volatility spillovers for these securities, and the results are presented in Table 4. The main information to be gleaned from Table 4 is the general decline in spillovers in relation to proportion of the fund. (Table 4 is sorted such that STK1 is the highest percentage holding of the ETF and STK10 is the smallest.) Spillovers in each column generally decline with the percentage of each stock in the ETF. This observation leads to a potential link among the levels of volatility spillovers to measures of ETF and stock liquidity as well as the relative proportions of each stock held by the ETF.

Volatility spillovers and liquidity

Given the significant levels of volatility spillovers observed in the previous section, we next examine how

volatility spillovers are related to measures of liquidity, the proportion of each component stock held in each ETF, as well as proxies for arbitrage activity and size. We use the daily volatility spillover time series’ as dependent variables in a series of regressions designed to measure the impact of liquidity and the proportion of each stock in its respective ETF on spillover levels.

Our first estimate of (il)liquidity is a time series analogue to the Amihud (2002) illiquidity measure, defined as:

$$\lambda_i = ILLIQ_{i,t} = \frac{1}{200} \sum_{t=-1}^{-200} \frac{|R_{i,t}|}{VOL_{i,t}} \quad (14)$$

where $|R_{i,t}|$ is the absolute value of daily return for each stock and ETF and $VOL_{i,t}$ represents daily ETF dollar turnover. A 200-day moving average is used so that it is comparable to the 200-day rolling estimates of volatility spillovers. In an extensive study of liquidity measures, Goyenko *et al.* (2009) find that this measure provides an accurate assessment of the price impact that is at least as effective as more recent and more complicated measures of liquidity. However, this exact measure cannot be used since volume (and dollar turnover) is not stationary in general, and clearly not stationary during the sample period. To eliminate the effect of the rising trend in turnover, Amihud’s (2002) mean-adjusted illiquidity is calculated by first averaging illiquidity for each of the 10 stocks in each ETF:

$$AILLIQ_t = \frac{1}{10} \sum_{i=1}^{10} ILLIQ_{i,t} \quad (15)$$

Mean-adjusted illiquidity for each stock and ETF is calculated as follows:

$$ILLIQ_{i,t} = \frac{ILLIQ_{i,t}}{AILLIQ_t} \quad (16)$$

This measure of illiquidity is not sensitive to the overall level of turnover and provides a good proxy for the relative illiquidities of the ETFs and their component stocks. We take the natural log of this measure for ease of interpretation and denote the illiquidity variable as $Illiq_{i,t}$.

As proposed in our motivating model, the level of volatility spillovers may also be related to the proportion of each stock contained in the ETFs. Thus our next variable of interest is the proportion of each component stock in each ETF (the a_i term in Equation 6) that is provided by the CRSP Mutual Fund Database. We also examine two variables that are also related to the arbitrage process for ETFs and their underlying stocks. First, the (absolute) per cent deviation from NAV is likely to induce arbitrage trading activities that may increase volatility spillovers. We also consider the flow of funds for the ETFs as a proxy for the creation/redemption process. Large flows into or out of ETFs are likely indicators of high arbitrage activities as APs trade baskets of stocks for ETFs (and vice versa) to net their positions. We calculate flow of funds for each ETF j as follows:

$$Flow\ of\ Funds_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + r_{j,t})}{TNA_{j,t}} \quad (17)$$

Finally, as suggested by Madura and Ngo (2008), we include ETF market capitalization in our estimations since they find stronger valuation effects for larger ETFs. The same effect may apply to volatility spillovers.

In order to estimate the relations among these variables and volatility spillovers, we estimate the following coefficients using the Fama and MacBeth (1973) procedure:

$$\begin{aligned} \ln(VolSpill_{i,t}) = & \alpha_i + \beta_1 STKIlliq_{i,t} \\ & + \beta_2 ETFIlliq_{i,t} \\ & + \beta_3 Proportion_{i,t} \\ & + \beta_3 DevNAV_{i,t} \\ & + \beta_4 FundsFlow_{i,t} \\ & + \beta_5 ETFMktCap_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (18)$$

We also substitute the stock and ETF $Illiq$ variables with dollar turnover (liquidity) in an alternative specification. The t -statistics are adjusted using the Newey and West (1987) procedure (with five lags to represent one week of trading activity), and the results of these regressions are presented in Table 5. In Panel A, the stock and ETF illiquidity coefficients β_1 and β_2 are statistically significant

Table 5. Directional volatility spillovers, liquidity and arbitrage

$$\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Illiq_{i,t} + \beta_2 ETF\ Illiq_{i,t} + \beta_3 Proportion_{i,t} + \beta_4 DevNAV_{i,t} + \beta_5 FundsFlow_{i,t} + \beta_6 ETFMktCap_{i,t} + \varepsilon_{i,t}$$

Panel A: illiquidity			Panel B: liquidity		
Explanatory variables	Coeff.	Estimate (t -Stat.)	Explanatory variables	Coeff.	Estimate (t -Stat.)
Stock illiquidity	β_1	-0.13*** (-12.80)	Stock liquidity	β_1	0.13*** (18.97)
ETF illiquidity	β_2	-0.20*** (-5.93)	ETF liquidity	β_2	0.45*** (16.48)
Proportion	β_3	0.04*** (5.89)	Proportion	β_3	0.05*** (7.07)
Deviation from NAV	β_4	0.17*** (7.45)	Deviation from NAV	β_4	0.19*** (9.16)
Flow of funds	β_5	0.30 (1.61)	Flow of funds	β_5	0.03 (0.18)
ETF market cap	β_6	0.17*** (2.78)	ETF market cap	β_6	0.06 (0.92)
Constant	α	-5.16*** (-10.16)	Constant	α	-11.63*** (-35.53)
Observations		225 455	Observations		226 440
Average R^2		0.421	Average R^2		0.410
Number of groups		2529	Number of groups		2529

Notes: Table 5 presents the results of Fama and Macbeth (1973) regressions of volatility spillovers on (il)liquidity and several variables that proxy for arbitrage activity. SEs are corrected for heteroscedasticity using the Newey and West (1987) procedure with five lags. The t -statistics from these estimations are presented in parentheses. *** represents statistical significance at the 1% level.

drivers of volatility spillovers from the ETFs to their largest component stocks. As proposed in our model, both coefficients are negative, reflecting decreasing (increasing) spillovers resulting from illiquidity (liquidity). Because the variables are expressed as logs, the estimation is easily interpreted, such that a 1% increase in stock illiquidity reduces volatility spillovers by 13 basis points. The comparable figure for ETF illiquidity is 20 basis points. In Panel B, we substitute our liquidity variable for illiquidity, and the coefficients are strong and positive, as expected. A 1% increase in stock (ETF) liquidity leads to a 0.13% (0.45%) increase in volatility spillovers. This provides an indication that liquidity in these ETFs plays significant role in the volatility generating process for their largest component stocks. And the effects of ETF (il)liquidity are greater than those of stock (il)liquidity for both of our measures. So although we cannot conclude that ETFs increase the volatility of these components, we can conclusively state that trading in these funds predicts future volatility innovations in their largest component stocks.

The coefficient estimates for proportion are positive in both specifications which is consistent with the intuition of our model. Volatility spillovers from ETFs to their largest component stocks are thus positively related to the percentage holding of each holding. The remaining coefficient estimates are similar in both specifications of our model, so we will only discuss those in Panel A in the interest of brevity. The coefficient for deviation from NAV is positive and significant, a clear indication that arbitrage activities may contribute to the volatility generating process of ETF component stocks. It is difficult to interpret the economic significance of this result, however, since arbitrage activities will occur only beyond certain economically significant levels due to frictions from the trading process. But the β_4 coefficients indicate significant positive effects. A 10 basis point increase in this variable leads to a 1.70% increase in spillovers. The coefficient for the absolute value of flow of funds is positive and significant, reflecting the large effect of the creation/redemption process on volatility spillovers. A 1% increase in this variable leads to a 0.30% increase in volatility spillovers, although it is only marginally significant at the 10% level. Finally, spillovers are higher among the component stocks of larger ETFs as indicated by the positive coefficient (β_6) for ETF market capitalization. This result parallels the finding of Madura and Ngo (2008) that component stocks of large ETFs experience more pronounced increases in trading volume at ETF inception, and we provide a link between increased volume and volatility. A 1% increase in this variable leads to a 0.39% increase in spillovers.

Robustness

As a robustness check to examine the differential effects of these variables on stocks of different sizes, we separate our sample into three groups: the top three, middle four and lowest three component stocks in terms of their proportions in each ETF. We then re-estimate Equation 18 for each of the three groups, and the results are presented in Table 6. For all three groups in Panel A, the coefficients for stock and illiquidity are negative and significant just as we observed in Table 5. Additionally, the spillover effects are greater for the larger stocks in the sample, which may reflect greater trading activity in these higher capitalization stocks relative to others in each ETF. Proportion remains positive for the middle component stocks as we saw in the full sample, but is insignificant for the largest stocks. However, although small compared to the middle group, the coefficient for the smallest stocks turns negative. Spillovers for these stocks actually decrease with proportion, and it seems that stocks must reach some level of 'critical mass' in order for ETF trading to have some effect. This effect is likely related to the relatively greater importance of flow of funds and ETF market capitalization on these stocks. These coefficients (β_5 and β_6) are particularly large for the smallest stocks, and these effects may be responsible for the seemingly anomalous proportion result, since proportion is negatively correlated to both of these variables (at -0.47 and -0.05 , respectively). The effects of ETF market capitalization are higher for the smallest stocks in the sample, which may be an indication that the growth of ETF trading does in fact increase volatility and that the effect is larger for smaller stocks. This result is once again consistent with Madura and Ngo (2008) and Clifford *et al.* (2014, forthcoming), who find differential size effects regarding ETF component stock valuation and fund flows, respectively. Flow of funds is not significant for the larger stocks, perhaps reflecting the inability of arbitrageurs to affect prices greatly. But once again, this variable is highly correlated with deviations from NAV (0.26), so the effects of funds flows may be subsumed by this related variable.

The results for the liquidity variables (raw dollar turnover) are presented in Panel B of Table 6 and are largely consistent in direction and size with earlier estimates. One final aspect to note in Table 6 is that the R^2 figures are, on average, about 8% higher than those in Table 5. So even though these estimations contain far fewer observations since we divide our sample into three subsets, the explanatory power of the models has increased when we account for differences in factor sensitivities due to company size.

Due to the fact that our sample period covers the financial crisis of the period 2007 to 2009, we include an additional robustness check that separates our time series

Table 6. Directional volatility spillovers, liquidity and arbitrage by proportion

Dependent variable		Top 3	Middle 4	Low 3
Explanatory variables	Coeff.	estimate (<i>t</i> -Stat.)	estimate (<i>t</i> -Stat.)	estimate (<i>t</i> -Stat.)
Panel A: illiquidity				
$\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Illiq_{i,t} + \beta_2 ETF\ Illiq_{i,t} + \beta_3 Proportion_{i,t} + \beta_4 DevNAV_{i,t} + \beta_5 FundsFlow_{i,t} + \beta_6 ETFMktCap_{i,t} + \varepsilon_{i,t}$				
Stock illiquidity	β_1	-0.12*** (-7.44)	-0.07*** (-3.84)	-0.10*** (-4.19)
ETF illiquidity	β_2	-0.25*** (-7.15)	-0.35*** (-7.61)	-0.08** (-2.45)
Proportion	β_3	0.00 (-0.30)	0.16*** (12.79)	-0.06*** (-4.75)
Deviation from NAV	β_4	0.12*** (5.24)	0.24*** (9.53)	0.12*** (5.43)
Flow of funds	β_5	0.13 (0.61)	0.31*** (1.34)	0.45** (2.29)
ETF market cap	β_6	0.17*** (-2.80)	0.14* (1.92)	0.33*** (5.49)
Constant	α	-5.42*** (-8.56)	-9.81*** (-13.44)	-2.16*** (-7.60)
Observations		67 363	90 377	67 715
Average R^2		0.481	0.513	0.469
Number of groups		2529	2529	2529
Panel B: liquidity				
$\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Turnover_{i,t} + \beta_2 ETF\ Turnover_{i,t} + \beta_3 Proportion_{i,t} + \beta_4 DevNAV_{i,t} + \beta_5 FundsFlow_{i,t} + \beta_6 ETFMktCap_{i,t} + \varepsilon_{i,t}$				
Stock liquidity	β_1	0.08*** (4.65)	0.09*** (5.32)	0.10*** (8.15)
ETF liquidity	β_2	0.48*** (16.26)	0.66*** (20.64)	0.35*** (11.22)
Proportion	β_3	0.01 (0.73)	0.19*** (16.04)	-0.03*** (-2.43)
Deviation from NAV	β_4	0.14*** (6.73)	0.19*** (7.30)	0.19*** (9.03)
Flow of funds	β_5	-0.12 (-0.58)	0.25 (1.16)	0.27 (1.29)
ETF market cap	β_6	0.24*** (2.85)	0.08 (1.09)	0.12* (1.77)
Constant	α	-11.94*** (-31.86)	-16.56*** (-38.36)	-8.52*** (-7.60)
Observations		67 560	90 905	67 975
Average R^2		0.496	0.498	0.437
Number of groups		2529	2529	2529

Notes: Table 6 presents the results of Fama and Macbeth (1973) regressions of volatility spillovers on component stock and ETF illiquidity and several variables that proxy for arbitrage activity. SEs are corrected for heteroscedasticity using the Newey and West (1987) procedure with five lags. The *t*-statistics from these estimations are presented in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

into three periods; pre-Crisis, crisis and post-Crisis. We define the financial crisis as the period when the TED spread (Treasury – Eurodollar, indicating confidence in the banking system) spikes first in July 2007 and then finally returns to more ‘normal’ levels in December 2009. The results of these estimations are contained in Table 7. In Panel A, the results are generally consistent

with the full-period results, with a few exceptions. First and foremost, the coefficient for stock illiquidity is positive in the pre-crisis period, and the coefficient for ETF illiquidity is positive for during the post-crisis period. Since we do not make a supposition regarding the correlations among stocks in each ETF, it is difficult to interpret these results, but it is most likely related to the correlations

Table 7. Directional volatility spillovers, liquidity and arbitrage by timeframe

Dependent variable		Pre-crisis	Crisis	Post-crisis
Explanatory variables	Coeff.	Estimate (<i>t</i> -Stat.)	estimate (<i>t</i> -Stat.)	estimate (<i>t</i> -Stat.)
Panel A: illiquidity				
$\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Illiq_{i,t} + \beta_2 ETF\ Illiq_{i,t} + \beta_3 Proportion_{i,t} + \beta_4 DevNAV_{i,t} + \beta_5 FundsFlow_{i,t} + \beta_6 ETFMktCap_{i,t} + \varepsilon_{i,t}$				
Stock illiquidity	β_1	0.06*** (4.24)	-0.22*** (-14.51)	-0.24*** (-26.77)
ETF illiquidity	β_2	-0.74*** (-36.12)	-0.24*** (-6.19)	0.20*** (4.21)
Proportion	β_3	0.20*** (14.18)	0.01** (2.31)	-0.05*** (-25.11)
Deviation from NAV	β_4	0.10*** (7.33)	0.21*** (10.31)	0.20*** (4.62)
Flow of funds	β_5	0.56*** (8.38)	0.73*** (5.01)	-0.01 (-0.02)
ETF market cap	β_6	-0.39*** (-5.83)	-0.12 (-1.12)	0.65*** (6.69)
Constant	α	-13.45*** (-35.47)	-5.80*** (-16.36)	0.90 (1.20)
Observations		78 886	34 035	112 534
Average R^2		0.494	0.502	0.345
Number of Groups		891	380	1258
Panel B: liquidity				
$\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Turnover_{i,t} + \beta_2 ETF\ Turnover_{i,t} + \beta_3 Proportion_{i,t} + \beta_4 DevNAV_{i,t} + \beta_5 FundsFlow_{i,t} + \beta_6 ETFMktCap_{i,t} + \varepsilon_{i,t}$				
Stock liquidity	β_1	0.12*** (12.38)	0.22*** (12.77)	0.11*** (10.90)
ETF liquidity	β_2	0.72*** (29.69)	0.35*** (11.90)	0.29*** (6.10)
Proportion	β_3	0.20*** (14.02)	0.03*** (4.22)	-0.04*** (-23.26)
Deviation from NAV	β_4	0.09*** (6.75)	0.17*** (8.57)	0.27*** (6.76)
Flow of funds	β_5	0.23** (2.40)	0.42** (2.44)	-0.22 (-0.59)
ETF market cap	β_6	-0.50*** (-6.40)	-0.18* (-1.86)	0.53*** (5.01)
Constant	α	-14.39*** (-43.47)	-11.02*** (-24.75)	-9.86*** (-7.60)
Observations		79 797	34 035	112 608
Average R^2		0.492	0.532	0.314
Number of groups		891	380	1258

Notes: Table 7 presents the results of Fama and Macbeth (1973) regressions of volatility spillovers on component stock and ETF illiquidity and several variables that proxy for arbitrage activity. SEs are corrected for heteroscedasticity using the Newey and West (1987) procedure with five lags. The *t*-statistics from these estimations are presented in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

among these securities. For instance, in regressions that do not include stock illiquidity (not reported), the coefficients for ETF illiquidity are negative and significant in all time periods. It is clear, however, that the effect of ETF illiquidity on volatility spillovers has declined since the large build-up in ETF trading volume and the financial crisis. The coefficients on ETF illiquidity are more consistent in

Panel B, where they also demonstrate a declining trend. The effects of proportion also seem to decline over time for both measures of illiquidity, and we see that same anomalous negative coefficient in the most recent period that we saw earlier for small stocks. The same pattern holds for flow of funds as it becomes insignificant in the most recent period. Conversely, the effect of the ETF size

becomes more pronounced in the most recent period. Finally, once again the R^2 figures are considerably higher in the subperiods than those for the full sample in Table 5.

V. Conclusion

The volatility-generating process of ETFs and their largest component stocks are analysed, based on the supposition that shocks to ETF prices, which may be driven by liquidity-seeking institutions, 'noise' traders or industry fundamentals, affect the volatility-generating process of their largest component stocks. Although we cannot conclusively state that ETFs add volatility to the stock market since market – and/or industry-wide information might be impounded into stock prices in the absence of ETFs, it is clear that these securities are now important to the volatility-generating process of their largest component stocks. Shocks to ETF prices, whether caused by arbitrage activity or liquidity seeking traders, are useful in modelling the future volatility processes of their largest holdings. There is a clear upward trend in volatility spillovers from the period 2003 to 2011, concurrent with the dramatic rise in ETF trading over this period. The level of spillovers has fallen since 2011 as trading volume in these ETFs has attenuated.

Volatility spillovers in these securities flow from ETFs to stocks and the level of volatility spillovers from ETFs to component stocks is positively related to ETF liquidity and the proportion of each stock that is held in the ETF. Significant volatility spillovers from sector ETFs to their component stocks are also driven by deviations from NAV, flow of funds and the market capitalization of the ETF. The effects are generally stronger for ETF components of smaller size, and the importance of each factor changes over time. The results are consistent with trading-based explanations of volatility, and they are relevant to market practitioners, regulators and investors in these increasingly popular products.

References

Admati, A. R. and Pfleiderer, P. (1988) A theory of intraday patterns: volume and price variability, *Review of Financial Studies*, **1**, 3–40. doi:10.1093/rfs/1.1.3

Alizadeh, S., Brandt, M. W. and Diebold, F. X. (2002) Range-based estimation of stochastic volatility models, *Journal of Finance*, **57**, 1047–91. doi:10.1111/1540-6261.00454

Amihud, Y. (2002) Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets*, **5**, 31–56. doi:10.1016/S1386-4181(01)00024-6

Avramov, D., Chordia, T. and Goyal, A. (2006) The impact of trades on daily volatility, *Review of Financial Studies*, **19**, 1241–77. doi:10.1093/rfs/hhj027

Bae, K.-H., Kang, J.-K. and Wang, J. (2012) The costs of ETF membership: valuation effect of ETFs on underlying firms,

Working Paper, Schulich School of Business. Available at <http://ssrn.com/abstract=2016531> (accessed 15 July 2014).

Ben-David, I., Franzoni, F. A. and Moussawi, R. (2014) Do ETFs increase volatility?, Working Paper, Ohio State University. Available at <http://ssrn.com/abstract=1967599> (accessed 15 July 2014).

Bessembinder, H. and Seguin, P. J. (1992) Futures-trading activity and stock price volatility, *Journal of Finance*, **47**, 2015–34. doi:10.1111/j.1540-6261.1992.tb04695.x

Blackrock, Inc. (2010) US ETF and ETP assets break through \$1 trillion milestone, *Press Release*, December 17.

Blackrock, Inc. (2011) ETF Landscape, *Industry Review*, August 16.

Bradley, H. and Litan, R. (2010) Choking the recovery: why new growth companies aren't going public and unrecognized risks of future market disruptions, Working Paper, Ewing Marion Kauffman Foundation. Available at <http://ssrn.com/abstract=1706174> (accessed 15 July 2014).

CFTC-SEC (2010a) *Preliminary Findings Regarding the Market Events of May 6, 2010, May 18, 2010*, US Government Printing Office, Washington, DC.

CFTC-SEC (2010b) *Findings Regarding the Market Events of May 6, 2010, September 30, 2010*, US Government Printing Office, Washington, DC.

Chan, K. (1992) A further analysis of the lead-lag relationship between the cash market and stock index futures market, *Review of Financial Studies*, **5**, 123–52. doi:10.1093/rfs/5.1.123

Chan, K. and Fong, W.-M. (2000) Trade size, order imbalance, and the volatility-volume relation, *Journal of Financial Economics*, **57**, 247–73. doi:10.1016/S0304-405X(00)00057-X

Chan, L. and Lien, D. (2003) Using high, low, open, and closing prices to estimate the effects of cash settlement on futures prices, *International Review of Financial Analysis*, **12**, 35–47. doi:10.1016/S1057-5219(02)00125-4

Chordia, T., Roll, R. and Subrahmanyam, A. (2002) Order imbalance, liquidity, and market returns, *Journal of Financial Economics*, **65**, 111–30. doi:10.1016/S0304-405X(02)00136-8

Clifford, C., Fulkerson, J. and Jordan, B. (2014, forthcoming) What drives ETF flows?, *Financial Review*.

Da, Z. and Shive, S. (2013) When the bellwether dances to noise: evidence from exchange-traded funds, Working Paper, University of Notre Dame. Available at <http://ssrn.com/abstract=2158361> (accessed 15 July 2014).

De Long, J. B., Shleifer, A., Summers, L. H. et al. (1990) Noise trader risk in financial markets, *Journal of Political Economy*, **98**, 703–38. doi:10.1086/261703

Diebold, F. X. and Yilmaz, K. (2009) Measuring financial asset return and volatility spillovers, with application to global equity markets, *The Economic Journal*, **119**, 158–71. doi:10.1111/j.1468-0297.2008.02208.x

Diebold, F. X. and Yilmaz, K. (2012) Better to give than to receive: predictive directional measurement of volatility spillovers, *International Journal of Forecasting*, **28**, 57–66. doi:10.1016/j.ijforecast.2011.02.006

Engle, R. (2002) New frontiers for arch models, *Journal of Applied Econometrics*, **17**, 425–46. doi:10.1002/jae.683

Engle, R., Gallo, G. and Velucchi, M. (2012) Volatility spillovers in East Asian financial markets: a MEM-based approach, *Review of Economics and Statistics*, **94**, 222–3. doi:10.1162/REST_a_00167

Fama, E. F. and Macbeth, J. D. (1973) Risk, return, and equilibrium: empirical tests, *Journal of Political Economy*, **81**, 607–36. doi:10.1086/260061

- Forbes, K. J. and Rigobon, R. (2002) No contagion, only interdependence: measuring stock market comovements, *Journal of Finance*, **57**, 2223–61. doi:10.1111/0022-1082.00494
- French, K. R. and Roll, R. (1986) Stock return variances: the arrival of information and the reaction of traders, *Journal of Financial Economics*, **17**, 5–26. doi:10.1016/0304-405X(86)90004-8
- Goyenko, R. Y., Holden, C. W. and Trzcinka, C. A. (2009) Do liquidity measures measure liquidity?, *Journal of Financial Economics*, **92**, 153–81. doi:10.1016/j.jfineco.2008.06.002
- Hamao, Y., Masulis, R. W. and Ng, V. (1990) Correlations in price changes and volatility across international stock markets, *Review of Financial Studies*, **3**, 281–307. doi:10.1093/rfs/3.2.281
- Hasbrouck, J. (2003) Intraday price formation in US equity index markets, *Journal of Finance*, **58**, 2375–99.
- Haugen, R. A. (2010) *The New Finance: Overreaction, Complexity and Uniqueness*, 4th edn, Prentice Hall, Upper Saddle River, NJ.
- Haugen, R. A., Talmor, E. and Torous, W. N. (1991) The effect of volatility changes on the level of stock prices and subsequent expected returns, *Journal of Finance*, **46**, 985–1007. doi:10.1111/j.1540-6261.1991.tb03774.x
- Hegde, S. P. and McDermott, J. B. (2004) The market liquidity of DIAMONDS, Q's, and their underlying stocks, *Journal of Banking and Finance*, **28**, 1043–67. doi:10.1016/S0378-4266(03)00043-8
- Johnson, T. L. and So, E. C. (2012) The option to stock volume ratio and future returns, *Journal of Financial Economics*, **106**, 262–86. doi:10.1016/j.jfineco.2012.05.008
- Jones, C. M., Kaul, G. and Lipson, M. L. (1994) Transactions, volume, and volatility, *Review of Financial Studies*, **7**, 631–51. doi:10.1093/rfs/7.4.631
- Koop, G., Pesaran, M. H. and Potter, S. M. (1996) Impulse response analysis in nonlinear multivariate models, *Journal of Econometrics*, **74**, 119–47. doi:10.1016/0304-4076(95)01753-4
- Kyle, A. S. (1985) Continuous auctions and insider trading, *Econometrica*, **53**, 1315–35. doi:10.2307/1913210
- Lin, W. L., Engle, R. F. and Ito, T. (1994) Do bulls and bears move across borders? International transmission of stock returns and volatility, *Review of Financial Studies*, **7**, 507–38. doi:10.1093/rfs/7.3.507
- Madhavan, A. (2011) Exchange-traded funds, market structure and the flash crash. Available at <http://ssrn.com/abstract=1932925> (accessed 15 July 2014).
- Madura, J. and Ngo, T. (2008) Impact of ETF Inception on the valuation and trading of component stocks, *Applied Financial Economics*, **18**, 995–1007. doi:10.1080/09603100701335424
- Malinova, K. and Park, A. (2010) Trading volume in dealer markets, *Journal of Financial and Quantitative Analysis*, **45**, 1447–84. doi:10.1017/S002210901000061X
- Newey, W. K. and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, **55**, 703–8. doi:10.2307/1913610
- Parkinson, M. (1980) The extreme value method for estimating the variance of the rate of return, *Journal of Business*, **53**, 61–5. doi:10.1086/296071
- Pesaran, H. H. and Shin, Y. (1998) Generalized impulse response analysis in linear multivariate models, *Economics Letters*, **58**, 17–29. doi:10.1016/S0165-1765(97)00214-0
- Roll, R., Schwartz, E. and Subrahmanyam, A. (2010) O/S: the relative trading activity in options and stock, *Journal of Financial Economics*, **96**, 1–17. doi:10.1016/j.jfineco.2009.11.004
- Shleifer, A. and Vishny, R. W. (1997) The limits of arbitrage, *Journal of Finance*, **52**, 35–55. doi:10.1111/j.1540-6261.1997.tb03807.x