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# Exchange-traded funds, liquidity and volatility

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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

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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 form 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 ($\lambda$) 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: $\tilde{P}_i^t = \tilde{\delta}_i^t + \lambda_i\left(\tilde{\omega}_i^t\right)$, where $\tilde{\delta}_i^t$ is the available information for stock $i$ at time $t$, $\lambda_i$ 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, arbitragers 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 ($\tilde{\varepsilon} \sim \left(0, \sigma_\varepsilon^2\right)$).

When a shock $\varepsilon$ is realized, price of the ETF will be:

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

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

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

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

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

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:

$$\frac{\Delta\omega_n}{\Delta\omega_1} = \frac{a_n}{a_1}, \ldots, \frac{\Delta\omega_n}{\Delta\omega_{n-1}} = \frac{a_n}{a_{n-1}}, \frac{\Delta\omega_n}{\Delta\omega_{ETF}} = a_n \tag{4}$$

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:

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

[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:

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

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 |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | 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)**

| Year | XLB Basic materials | XLE Energy | XLF Financials | XLI Industrials | XLK Technology | XLP Consumer staples | XLU Utilities | XLV Health care | XLY Consumer discretionary |
|---|---|---|---|---|---|---|---|---|---|
| 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:

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

Using a moving average representation, this expression becomes:

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

where

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_5 A_{i-5} \tag{9}$$

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 $x_j \forall \neq i$ 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,…,$N$, 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,…,$N$, 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,…:

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

The variance matrix for the error vector $\varepsilon$ is denoted by $\Sigma$, and the SD of the error term for the $j$th equation is $\sigma_{jj}$. 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:

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

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

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

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{12}$$

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:

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

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 $\hat{\sigma}_{it} = 100\sqrt{255 \cdot \tilde{\sigma}_{it}^{2}}$. 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 | XLY | All |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | 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:

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

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 $\hat{\sigma}_{it} = 100\sqrt{255 \cdot \tilde{\sigma}_{it}^2}$.

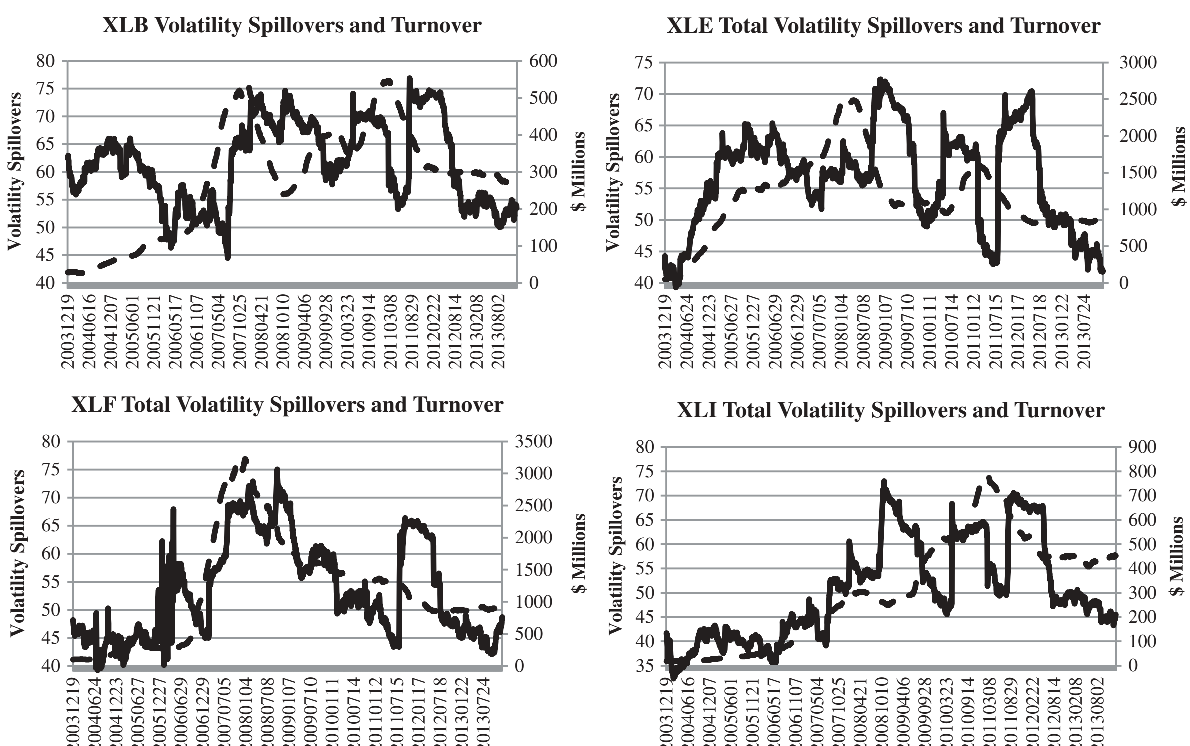


**Fig. 1. This figure shows the *total volatility spillover indexes* for each of the ETFs and their respective component stocks, as in Diebold and Yilmaz (2012). The time series estimates are presented here using a 200-day rolling estimation period, five lags in the VARs and a 10-day forecast horizon. 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 | XLY |
| | 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 |
| To | 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:

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

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:

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

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

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

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 $\beta_1$ and $\beta_2$ 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 | $\beta_1$ | −0.13*** (−12.80) | Stock liquidity | $\beta_1$ | 0.13*** (18.97) |
| ETF illiquidity | $\beta_2$ | −0.20*** (−5.93) | ETF liquidity | $\beta_2$ | 0.45*** (16.48) |
| Proportion | $\beta_3$ | 0.04*** (5.89) | Proportion | $\beta_3$ | 0.05*** (7.07) |
| Deviation from NAV | $\beta_4$ | 0.17*** (7.45) | Deviation from NAV | $\beta_4$ | 0.19*** (9.16) |
| Flow of funds | $\beta_5$ | 0.30 (1.61) | Flow of funds | $\beta_5$ | 0.03 (0.18) |
| ETF market cap | $\beta_6$ | 0.17*** (2.78) | ETF market cap | $\beta_6$ | 0.06 (0.92) |
| Constant | $\alpha$ | −5.16*** (−10.16) | Constant | $\alpha$ | −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 $\beta_4$ 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 ($\beta_6$) 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 ($\beta_5$ and $\beta_6$) 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 (*t*-Stat.) | estimate (*t*-Stat.) | estimate (*t*-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 | $\beta_1$ | −0.12*** | −0.07*** | −0.10*** |
| | | (−7.44) | (−3.84) | (−4.19) |
| ETF illiquidity | $\beta_2$ | −0.25*** | −0.35*** | −0.08** |
| | | (−7.15) | (−7.61) | (−2.45) |
| Proportion | $\beta_3$ | 0.00 | 0.16*** | −0.06*** |
| | | (−0.30) | (12.79) | (−4.75) |
| Deviation from NAV | $\beta_4$ | 0.12*** | 0.24*** | 0.12*** |
| | | (5.24) | (9.53) | (5.43) |
| Flow of funds | $\beta_5$ | 0.13 | 0.31*** | 0.45** |
| | | (0.61) | (1.34) | (2.29) |
| ETF market cap | $\beta_6$ | 0.17*** | 0.14* | 0.33*** |
| | | (−2.80) | (1.92) | (5.49) |
| Constant | $\alpha$ | −5.42*** | −9.81*** | −2.16*** |
| | | (−8.56) | (−13.44) | (−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 | | | | |
| $\ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Turnover_{i,t} + \beta_2 ETF\ Turnover_{i,t} + \beta_3 Proportion_{i,t} + \beta_3 DevNAV_{i,t} + \beta_4 FundsFlow_{i,t} + \beta_5 ETFMktCap_{i,t} + \varepsilon_{i,t}$ | | | | |
| Stock liquidity | $\beta_1$ | 0.08*** | 0.09*** | 0.10*** |
| | | (4.65) | (5.32) | (8.15) |
| ETF liquidity | $\beta_2$ | 0.48*** | 0.66*** | 0.35*** |
| | | (16.26) | (20.64) | (11.22) |
| Proportion | $\beta_3$ | 0.01 | 0.19*** | −0.03*** |
| | | (0.73) | (16.04) | (−2.43) |
| Deviation from NAV | $\beta_4$ | 0.14*** | 0.19*** | 0.19*** |
| | | (6.73) | (7.30) | (9.03) |
| Flow of funds | $\beta_5$ | −0.12 | 0.25 | 0.27 |
| | | (−0.58) | (1.16) | (1.29) |
| ETF market cap | $\beta_6$ | 0.24*** | 0.08 | 0.12* |
| | | (2.85) | (1.09) | (1.77) |
| Constant | $\alpha$ | −11.94*** | −16.56*** | −8.52*** |
| | | (−31.86) | (−38.36) | (−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 ($t$-Stat.) | estimate ($t$-Stat.) | estimate ($t$-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 | $\beta_1$ | 0.06*** | −0.22*** | −0.24*** |
| | | (4.24) | (−14.51) | (−26.77) |
| ETF illiquidity | $\beta_2$ | −0.74*** | −0.24*** | 0.20*** |
| | | (−36.12) | (−6.19) | (4.21) |
| Proportion | $\beta_3$ | 0.20*** | 0.01** | −0.05*** |
| | | (14.18) | (2.31) | (−25.11) |
| Deviation from NAV | $\beta_4$ | 0.10*** | 0.21*** | 0.20*** |
| | | (7.33) | (10.31) | (4.62) |
| Flow of funds | $\beta_5$ | 0.56*** | 0.73*** | −0.01 |
| | | (8.38) | (5.01) | (−0.02) |
| ETF market cap | $\beta_6$ | −0.39*** | −0.12 | 0.65*** |
| | | (−5.83) | (−1.12) | (6.69) |
| Constant | $\alpha$ | −13.45*** | −5.80*** | 0.90 |
| | | (−35.47) | (−16.36) | (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 | | | | |
| $ln(VolSpill_{i,t}) = \alpha_i + \beta_1 STK\ Turnover_{i,t} + \beta_2 ETF\ Turnover_{i,t} + \beta_3 Proportion_{i,t} + \beta_3 DevNAV_{i,t} + \beta_4 FundsFlow_{i,t} + \beta_5 ETFMktCap_{i,t} + \varepsilon_{i,t}$ | | | | |
| Stock liquidity | $\beta_1$ | 0.12*** | 0.22*** | 0.11*** |
| | | (12.38) | (12.77) | (10.90) |
| ETF liquidity | $\beta_2$ | 0.72*** | 0.35*** | 0.29*** |
| | | (29.69) | (11.90) | (6.10) |
| Proportion | $\beta_3$ | 0.20*** | 0.03*** | −0.04*** |
| | | (14.02) | (4.22) | (−23.26) |
| Deviation from NAV | $\beta_4$ | 0.09*** | 0.17*** | 0.27*** |
| | | (6.75) | (8.57) | (6.76) |
| Flow of funds | $\beta_5$ | 0.23** | 0.42** | −0.22 |
| | | (2.40) | (2.44) | (−0.59) |
| ETF market cap | $\beta_6$ | −0.50*** | −0.18* | 0.53*** |
| | | (−6.40) | (−1.86) | (5.01) |
| Constant | $\alpha$ | −14.39*** | −11.02*** | −9.86*** |
| | | (−43.47) | (−24.75) | (−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 il(liquidity), 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.

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