Journal of Empirical Finance 43 (2017) 59–73

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

Determinants of price discovery in the VIX futures market

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ARTICLE INFO

JEL Classification:
C32
G01
G14

Keywords:
Price discovery
VIX
VIX futures
Futures basis
Information shares

ABSTRACT

We utilize the respective information share and common factor component weight approaches of Hasbrouck (1995) and Gonzalo and Granger (1995) to examine price discovery competition between the VIX and VIX futures. Our results show that VIX futures prices play a dominant role in the overall process of price discovery. An increase in the price difference between the VIX and VIX futures, commonly referred to as the futures basis, causes a corresponding increase in the contribution to price discovery made by VIX futures. Our empirical results also show that news announcements on macro-economic issues in the United States increase the dominant role of VIX futures in the overall process of price discovery. This dominant role remains unchanged when compared to VIX exchange-traded products and the volatility indices on non-US equity exchange-traded funds.

1. Introduction

Theoretically, no lead–lag relation should exist between the spot and futures markets in a perfectly efficient market. Nonetheless, in terms of real-world spot and futures prices, futures markets are likely to incorporate information more efficiently than spot markets due to futures markets' inherent leverage, low transaction costs, and the absence of any short-selling constraints (Stoll and Whaley, 1988; Wahab and Lashgari, 1993; Iihara et al., 1996; Koutmos and Tucker, 1996; Pizzi et al., 1998; Tse, 1999; Booth et al., 1999; Brooks et al., 2001; Hasbrouck, 2003; Covrig et al., 2004; Chou and Chung, 2006; Gaul and Theissen, 2008). Price discovery in the futures markets is commonly recognized as the use of futures prices to determine expectations in spot market prices (Schroeder and Goodwin, 1991; Yang et al., 2012). Price discovery in futures markets is an important issue that continues to receive considerable attention in the related finance literature.

We examine whether the intraday price discovery of VIX futures prices contributes to the efficiency of the Chicago Board Options Exchange Volatility Index (CBOE VIX). We also investigate the determinants of price discovery for VIX futures. The CBOE VIX is compiled from a portfolio of S & P 500 index options to assist in the approximation of the expected aggregate volatility of the S & P 500 index during the subsequent 30-calendar-day period. As a result of increasing demand for practical market risk management, VIX futures volume has increased sharply since its inception, especially after the introduction of VIX options.

The traditional view on the speed of adjustment of asset prices in response to the arrival of new information is that the degree of leverage, transaction costs, asset price volatility, and liquidity across markets that trade almost homogeneous assets determine the difference in market responses. Liquidity and transaction costs are most commonly studied as factors that influence price discovery in the various futures markets. In the equity index futures market, Ates and Wang (2005) find that for the S & P 500 and Nasdaq 100 indices, the joint effects of operational efficiency and relative liquidity determined that electronic trading made a greater contribution to price discovery relative to open-outcry. Following a reduction in the minimum tick size in the stock market, Chen and Gau (2009)

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http://dx.doi.org/10.1016/j.jempfin.2017.05.002
Received 23 March 2016; Received in revised form 13 April 2017; Accepted 22 May 2017
Available online 24 May 2017
0927-5398/

note a reduction in the bid–ask spreads of the component stocks of the stock index, along with a corresponding increase in the contribution of the spot market to price discovery. Furthermore, Wang et al. (2013) find that the relative liquidity between regular and mini index TAIFEX futures affects the price discovery of the latter. In the stock options market, Chakravarty et al. (2004) find that price discovery in the options market is positively related to relative trading volume, relative bid–ask spreads, and underlying volatility. In the Treasury futures market, Mizrach and Neely (2008) and Fricke and Menkhoff (2011) show that the relative bid–ask spreads, trading volume, and realized volatility each have a statistically significant effect on price discovery in the US market. Finally, in the foreign exchange futures market, Chen and Gau (2010) find that the currency futures market makes a greater contribution to price discovery when the futures market is more liquid. Given the unique characteristics of volatility asset classes, we contribute to the literature by examining the role of the VIX futures basis—that is, the difference between a VIX futures price and the spot VIX index—in volatility price discovery.

The measure of the VIX futures basis is defined as the level of the VIX index minus the price of the nearest VIX futures contract. The level of the spot VIX represents the risk-neutral expected 30-day market volatility conditional on today's information, whereas the prices of VIX futures are based on the current expectation of what the expected 30-day market volatility will be on the futures expiration date. In other words, VIX futures basis measures the difference between the market's short-term volatility expectation and the relatively longer-term expected volatility and thus may capture information about the slope of the volatility term structure under the risk-neutral measure. Johnson (in press), building on work by Mixon (2007), finds that the slope of the VIX term structure predicts returns for volatility derivatives. Consequently, we investigate whether the VIX futures basis also plays a role in volatility price discovery.

Previous research finds that the mean reversion in volatility may affect the magnitude of the VIX futures basis. Numerous prior theoretical studies, including Lu and Zhu (2010), Zhang et al. (2010), Dupoyet et al. (2011), and Huskaj and Nossman (2013), suggest the inclusion of the mean-reverting property in modeling term structure dynamics. For example, the VIX futures basis typically increases after a big market drop because the spot VIX index spikes and then slowly reverts to its long-run mean. Hibbert et al. (2008) and Da et al. (2015) show that the behavior of investors tends to lead to excess volatility in the short run; that is, during a period of market crisis, the behavioral biases of investors are likely to cause a significant spike in the spot VIX index. The difference between short- and long-term volatility expectations cannot be easily eliminated by arbitrage activities, due to the non-tradable characteristic of the spot VIX. Investors cannot directly trade the spot VIX and have difficulty achieving timely replication of the VIX. Although the literature widely accepts that the value of the VIX is derived from the market prices of a portfolio of S & P 500 index options, it is not simply a weighted sum of the underlying options because the S & P 500 index options, from which the VIX is computed, sum the square of the VIX, not the VIX itself. As such, investors cannot easily buy or sell a basket of index options with expiration prices that are equal to the index, essentially because of the non-linear transformation. As a result, the contribution of the VIX to price discovery may be reduced.

We adopt Hasbrouck's (1995) information share approach, which requires the estimation of a vector error correction (VEC) model, and Gonzalo and Granger's (1995) common factor component weight approach for our analysis. We use these two approaches, which have been widely used to explore the extent of price discovery, to explore intraday price discovery in the VIX and VIX futures markets (e.g., Mizrach and Neely, 2008; Fricke and Menkhoff, 2011; Forte and Pena, 2009; Chen and Gau, 2010; Chang et al. 2013; Chakravarty et al., 2004). The sample period from May 3, 2004 to August 30, 2011 and includes newly established and rapidly growing VIX derivatives markets.

The information share and common factor component weight approaches provide a better understanding of the contribution of a market to price discovery. Therefore, we examine time-varying price discovery based on the calculation of both the daily information share and the common factor component weight measures. Our empirical findings show that the average information share (common factor component weight) of VIX futures is approximately 2.70 (2.83) times greater than that of the spot VIX, thereby providing strong support for the leading role of VIX futures in the overall price discovery process. The VIX futures basis is positively related to both the information share and the common factor component weight of VIX futures, at a level of significance of at least 5 percent. In other words, when the VIX futures basis is more positive, representing a downward-sloping term structure where the spot VIX index is higher than the VIX futures contract, price discovery in the VIX spot (futures) markets decreases (increases).

Given a theoretical linkage between the VIX index and S & P 500 index options, the high-frequency properties of S & P 500 index options may affect the importance of the role of the futures basis on intraday price discovery. Jiang and Tian (2007), for example, find that when high-frequency S & P 500 index option prices are used, systematic overestimation occurs in the measurement of the VIX during periods of rapid market movement. To overcome the problem of overestimation, several recent studies suggest the use of corridor implied volatility because it is likely unrelated to the liquidity of the S & P 500 index options market (e.g., Andersen and Bondarenko, 2007; Andersen, Bondarenko, and Gonzalez-Perez, 2015; Dotsis and Vlastakis, 2016). Our empirical results remain unchanged when using corridor implied volatility. In addition, in unreported tests, we use corridor implied volatility to calculate the futures basis instead of the VIX and find a significantly positive relation between price discovery and VIX futures.[1] The CBOE switched to the use of S & P weekly options to calculate the VIX, when appropriate, on October 6, 2014, to reduce some measurement biases.

More interestingly, we find an increase in the contribution made by VIX futures prices to the overall process of price discovery during periods of macroeconomic announcements in the United States, particularly with regard to the consumer price index (CPI;

[1] Results are available on request. We thank Professor Grigory Vilkov for sharing the Matlab codes to compute the measure of corridor implied volatility (http://www.vilkov.net/).

Nikkinen et al., 2007; Chen and Clements, 2007; Vähämaa and Äijö, 2011). In other words, the release of macroeconomic information is accompanied by a decline in the contribution to price discovery by the spot VIX. This finding is consistent with the notion that announcements on macroeconomic issues create economic uncertainty, leading to a short-term jump in the spot VIX index, with a resulting temporary move in VIX prices away from the equilibrium volatility price.

Our empirical results also reveal that longer contract maturity periods correspond to a reduction in the contribution of VIX futures to volatility price discovery. Furthermore, VIX futures prices play a dominant role in the overall process of price discovery even when compared to VIX exchange-traded products (ETPs) and the volatility indices on non-US equity exchange-traded funds (ETFs).

Prior studies do not provide a consensus on the long-run relation between the VIX and VIX futures. For example, Shu and Zhang (2012) identify one cointegration between the two series. In contrast, Frijns et al. (2016) find that the VIX and VIX futures at a sampling frequency of 15 seconds are both stationary processes. In other words, the stationarity of volatility appears to be largely dependent upon the sample period and the sampling frequency. In the study, we regard the information share and common factor component weight approaches as appropriate for the examination of volatility price discovery because of the detection of a cointegration relationship between VIX and VIX futures.[2]

This paper extends the studies of Shu and Zhang (2012) and Frijns et al. (2016) in four ways. First, we provide a more comprehensive analysis of the dynamic price discovery process for VIX and VIX futures intraday data. Shu and Zhang test the Granger causal relation between VIX futures prices and the VIX index using daily data from March 26, 2004 to May 20, 2009, and Frijns et al. (2016) conduct Granger causality analysis between these two intraday price series only using the predetermined sampling frequency.[3] In contrast, our price discovery analysis adopts the more robust sampling method of Chaboud et al. (2010). In addition, after detecting a cointegrating relation, we use both Hasbrouck's (1995) information share approach and Gonzalo and Granger's (1995) common factor component weight approach to investigate intraday price discovery in the VIX and VIX futures markets.

Second, whereas Frijns et al. (2016) uses liquidity measures and VIX changes, we show that the VIX futures basis is an important factor for the price discovery of market volatility. This finding sheds light on the construction of volatility trading strategies for practitioners. For example, traders can take a long position in VIX futures contracts with a short S & P futures position when the basis is extremely positive.

Third, to the best of our knowledge, our study is the first to empirically examine the effect of US macroeconomic news announcements and the interaction effect of macro announcements with futures basis on the volatility price discovery. We show that macro-news announcements enhance the impact of futures basis in VIX futures' price discovery. This result may be due to the overreaction of short-term volatility to macroeconomic news announcement surprises.

Finally, our investigation of the role of VIX ETPs and non-U.S. volatility ETFs in volatility price discovery complements the findings of Shu and Zhang (2012) and Frijns et al. (2016). Our empirical results show the dominant role of VIX futures in volatility price discovery is unchanged even if VIX ETPs and the non-US volatility ETFs are taken into account.

The remainder of this paper is organized as follows. Section 2 provides an explanation of the data and methodology adopted for this study. Section 3 gives descriptions of VIX futures basis and measures of volatility price discovery. Section 4 presents and discusses the empirical results. Finally, Section 5 offers some conclusions.

2. Data

The CBOE VIX is compiled from the market prices of S & P 500 index options and provides a method of approximating the expected aggregate volatility of the S & P 500 index during the subsequent 30-calendar-day period. As such, the VIX represents the aggregate information implied from the S & P 500 options market. VIX futures contracts were introduced in March 2004 to offer investors a simpler and more direct channel for trading market volatility without dealing with other associated risk factors that can significantly affect the overall performance of volatility strategies.

Data are obtained from CQG Market Data and comprise the intraday VIX levels and VIX futures tick information. The sample period runs from May 3, 2004 to August 30, 2011. The data set provides one-minute spot VIX values, whereas complete information is available for each trade quote and transaction in VIX futures, including the formation date, formation time (in minutes), expiration date, bid and ask prices for a quote or trading price, and transaction volume.

We match five-minute trading prices from the VIX index and VIX futures. Given that the sampling frequency and sample size of intraday returns (i.e., market microstructure features) can potentially affect the estimates of daily volatility or price discovery, we compute the average autocorrelation functions of VIX futures returns sampled at different frequencies. Panels A and B of Table 1 report the results for VIX index spot and futures returns, respectively (cf. Chaboud et al. 2010, Figure 6). The autocorrelations for VIX futures returns sampled at five-minute frequencies are lower, in absolute value terms, than those sampled at other frequencies. In unreported tests, we also compute daily information shares and common factor component weights at one-minute frequency and find that the leading role of VIX futures in price discovery remains unchanged. Therefore, this study uses five-minute frequency data.[4]

[2] Hasbrouck (1995) point out that the lead-lag effect is not appropriate when cointegration is present between two price series. Moreover, such estimations can easily mislead in the price discovery analysis.

[3] We thank an anonymous reviewer for suggesting the method of Chaboud et al. (2010).

[4] Results are available on request. We thank an anonymous referee for calling our attention to the issue of sampling frequency.

Table 1
Autocorrelation functions of VIX index returns sampled at selected frequencies.

No. of Lags	Frequencies				
	1-min	3-min	5-min	10-min	15-min
Panel A: Autocorrelation functions of VIX index spot returns					
1	0.483	0.443	−0.006	0.311	0.241
2	−0.053	−0.071	−0.002	−0.130	−0.089
3	−0.069	−0.078	−0.006	−0.016	−0.021
4	−0.028	−0.038	0.000	0.037	−0.074
5	−0.027	−0.056	0.008	−0.066	−0.018
6	−0.020	−0.042	0.016	−0.068	−0.046
7	−0.031	0.018	0.011	0.006	−0.006
8	−0.019	−0.025	−0.006	−0.033	−0.056
9	−0.040	−0.074	−0.008	−0.037	−0.009
10	−0.021	−0.006	0.007	0.003	−0.031
Panel B: Autocorrelation functions of VIX futures returns					
1	0.087	−0.031	−0.013	−0.048	−0.142
2	−0.003	−0.015	−0.017	−0.014	−0.247
3	0.003	−0.267	0.020	−0.391	0.006
4	−0.008	−0.017	0.007	−0.052	0.025
5	0.008	0.022	−0.010	0.065	0.088
6	−0.002	0.014	−0.018	−0.003	−0.126
7	−0.230	0.086	−0.014	0.114	0.019
8	−0.094	0.002	0.015	−0.090	−0.025
9	−0.011	−0.127	−0.006	−0.021	0.010
10	−0.007	−0.113	0.005	0.032	0.029

Note: The sample period runs from May 3, 2004 to August 30, 2011.

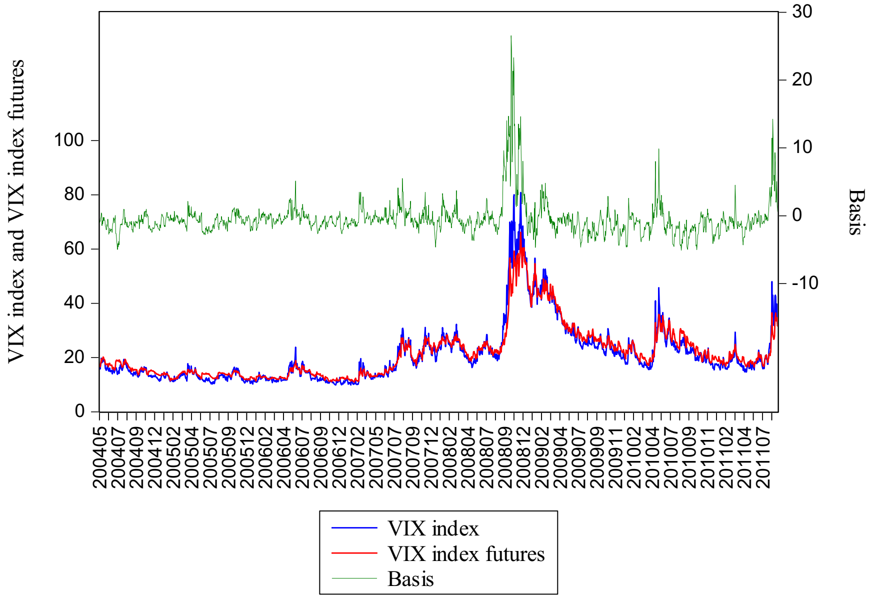

Fig. 1. VIX index, VIX futures, and futures basis, 2004–2011.

We use VIX futures prices from nearby contracts up to the eighth trading day prior to the expiration date to avoid the issue of liquidity imposed on shorter maturity futures. When the time-to-maturity of the nearest VIX futures contracts is less than eight days, we use the second-nearest contracts. Fig. 1 illustrates the VIX, VIX futures, and futures basis series (compiled from VIX index − VIX futures price). The figure shows that both VIX and VIX futures move in the same direction and exhibit mean reversion.

During the financial crisis period (September 2008–June 2009), the VIX index shifted to a much higher level than that of VIX futures. Therefore, we expect that VIX futures prices are more stable than the spot VIX index, particularly during a period of financial crisis. This higher stability of VIX futures prices is in line with Shu and Zhang (2012) who show that volatility follows a mean-reversion, with higher current volatility associated with lower future volatility. The futures basis is relatively higher during a period of financial crisis, reflecting the different perspectives on market conditions, from short- to long-term horizons.

3. Research methodology

3.1. A simple numerical example of the VIX futures basis under a stochastic volatility model

We theoretically introduce the VIX futures basis with a simple stochastic volatility model without jumps under a risk-neutral measure. Assume that the price dynamics of the S & P 500 index are represented as

$$\begin{aligned} dS_t &= rS_t dt + \sqrt{V_t} S_t dZ_s^Q, \\ dV_t &= \kappa(\theta_t - V_t)dt + \sigma_v \sqrt{V_t} dZ_v^Q, \\ d\theta_t &= \sigma_\theta dZ_\theta^Q, \end{aligned} \tag{1}$$

where S_t is the underlying S & P 500 index at time t; V_t is the variance rate at time t; σ_v represents the volatility of variance; r is the risk-free rate; κ is the speed of mean-reverting in variance; θ_t is the long-run mean level of variance given by the assumption of a normal distribution; Z_θ^Q is assumed to be independent of the two stochastic processes, $Z_s{}^Q$ and $Z_v{}^Q$; and ρ is the correlation coefficient between $Z_s{}^Q$ and $Z_v{}^Q$.

Zhang et al. (2010) derive the VIX index at time t and the price of VIX futures at time t with maturity T in a stochastic volatility environment. Therefore, we model the VIX futures basis as

$$\begin{aligned} Basis_t &\equiv VIX_t - F_t^T, \\ VIX_t &= 100 \times \sqrt{(1-C)\theta_t + CV_t},\ \tau_0 = 30/365, \\ F_t^T &= 100 \times E_t^Q[\sqrt{(1-C)\theta_T + CV_T}], \\ C &= \frac{1 - e^{-\kappa\tau_0}}{\kappa\tau_0}. \end{aligned} \tag{2}$$

Eq. (2) shows that the instantaneous variance of the S & P 500 index, the mean-reverting speed of the variance, the long-term mean level of the variance, and the volatility of variance affect the magnitude of the VIX futures basis.

Next, we provide a simple numerical example. Given the two parameters of the variance process as $\kappa = 2.4208$ and $\theta = 0.03774$ (Zhang et al., 2010), the VIX index (VIX futures basis) is roughly 11.22 (−1.96), with instantaneous volatility at 10%. When instantaneous volatility jumps from 10% to 50%, the VIX index (VIX futures basis) equals 47.98 (3.64). This sharp increase in the VIX potentially supports the results of Da et al. (2015), who find that investor behavioral biases creates excess volatility in the short run. In addition, using daily and intraday data, Hibbert et al. (2008) find that the behavioral biases of investors (i.e., the representativeness, effect, and extrapolation biases of such investors) triggers a major spike in implied/realized volatility, leading to a fall in asset price. Ultimately, short-term negative asymmetric relation exists between market returns and volatility. However, although short-term volatility increases sharply, the mean-reverting volatility has a relatively small effect on long-run volatility expectations. As a result, the sign changes for the VIX futures basis.[5] In other words, excess volatility in the short run caused by investor behavioral biases leads to a decrease (increase) in price discovery in the VIX spot (futures) markets. This finding provides the basis for our subsequent empirical analyses.

3.2. Measuring price discovery

To examine price discovery in the VIX index and VIX index futures, we use Hasbrouck's (1995) information share approach and Gonzalo and Granger's (1995) common factor component weight approach. The VIX index and VIX futures prices are driven by the same fundamental information; therefore, they should be closely related to common factors.

Shu and Zhang (2012) find that spot VIX and VIX futures prices are cointegrated and characterized by a long-term (or equilibrium) relation. Hasbrouck (1995) measures the contribution of a market to price discovery in terms of the information share, which is defined as the proportion of the efficient price innovation variance attributable to that market. If N market prices are driven by one common stochastic trend, then $N-1$ cointegrating or independent linear relations exist between them. Following Engle and Granger (1987), we use a VEC model to capture the dynamics in returns across N markets, as

$$\Delta p_t = \alpha z_{t-1} + A_1 \Delta p_{t-1} + A_2 \Delta p_{t-2} \cdots A_k \Delta p_{t-k} + \varepsilon_t, \tag{3}$$

where p_t is the $N \times 1$ vector of prices; $N \times N$ matrices A_i ($i = 1, 2, ..., k$) are the autoregressive coefficient matrices; $z_{t-1} = \beta' p_{t-1}$ is the $(N-1) \times 1$ error correction vector relating to the cointegrating vector β; α is the $N \times (N-1)$ adjustment coefficient matrix, which measures the ways in which prices react to the deviation from long-run equilibrium; and ε_t represents the vector of innovations as an $N \times 1$ vector of zero mean disturbances with the covariance matrix, Ω.

We rewrite the VEC model as a vector moving average (VMA) model as

$$\Delta p_t = \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots, \quad \text{where} \quad \Psi_0 = I, \tag{4}$$

where I denotes the $N \times N$ identity matrix, and sum of the VMA coefficients is defined as $\Psi(1)$.

When N prices are cointegrated with a rank of $N-1$, all rows of $\Psi(1)$ are identical (Hasbrouck, 1995). Let ψ be the common row

[5] Engle and Patton (2001) state on page 239, "Mean reversion in volatility implies that current information has no effect on the long-run forecast."

of Ψ(1); as defined by Hasbrouck (1995), the information share of one market is

$$IS^i = \frac{\psi_i^2\ \Omega_{ii}}{\psi\ \Omega\psi'}, \tag{5}$$

where ψ_i is the ith element of ψ, and Ω_{ii} is the (i, i) element of Ω. If the matrix Ω is not diagonal, we can only calculate a range of information shares and not a specific estimate.

Suppose that $\Omega = FF'$, where F is a lower triangular matrix. The information share of market i can then be calculated as

$$IS^i = \frac{[(\psi\ F)_i]^2}{\psi\ \Omega\psi'}, \tag{6}$$

where $(\psi F)_i$ is the ith element of ψF.

As previously noted, we can only calculate the upper and lower bounds of the Hasbrouck (1995) information share. However, Baillie et al. (2002) provide various examples to demonstrate that the average of the information shares provides a reasonable estimate of the contribution of a market to price discovery. We therefore use the average value of the information shares to compare the relative contribution of the spot VIX and VIX futures markets to price discovery.

Alternatively, Gonzalo and Granger (1995) decompose the vector of market prices into permanent ($f_t = f_t = \alpha'_\perp p_t\ p_t$) and transitory ($Z_t = \beta' p_{t-1}$) components. $f_t = \alpha'_\perp p_t$ vector is the common factor coefficient vector, which is orthogonal to α. It is the vector of the coefficients on the error-correction terms in Eq. (3). The ith element of $f_t = \alpha'_\perp p_t$, denoted as CC^i, measures the overall contribution of market i to price discovery. CC^i effectively gauges the contribution of each market price to the common permanent component. For practical purposes, we normalize this process to add to 1.

To determine the time-varying contributions to price discovery made by the VIX spot and VIX futures, we use five-minute daily data on the VIX spot and futures prices for our calculation of the daily IS^i (CC^i), for $i = S$ or F. Because higher sampling frequency and larger sample size of intraday returns can affect the estimates of daily volatility or price discovery (i.e. the presence of market microstructure features), we follow the approach of Chaboud et al. (2010) to compute the autocorrelation functions of the VIX index futures returns sampled at different frequencies. The autocorrelations for VIX futures returns sampled at five-minute frequencies are lower, in absolute value terms, than those sampled at other frequencies. This result suggests that the five-minute period is the appropriate frequency to examine price discovery. Indeed, it may potentially reduce the market microstructure effect. We also recalculate the daily information shares and common factor component weights of the VIX index and VIX index futures at one-minute frequencies and find that the leading role of VIX futures in the price discovery process holds. Due to space constraints, the results are not reported here.[6] The daily IS^i (CC^i) of the VIX futures market illustrates the way in which daily price discovery varies with market quality and the futures basis.

4. Empirical results

4.1. Summary statistics on the VIX and VIX futures

Table 2 provides the summary statistics for five-minute changes in the VIX, VIX futures, and the futures basis, where VIX and VIX futures returns are calculated by the difference in the log index level. Although the average VIX and VIX futures returns are very close, the standard deviation in the VIX returns is over twice the size of the standard deviation in the VIX futures returns. In other words, VIX futures prices are more stable than the spot VIX index. In addition, the mean of the futures basis is negative and in contango. Furthermore, as expected, each of the three series has positive skewness, excess kurtosis, and significant autocorrelation.

We also utilize the jump detection approach of Barndorff-Nielsen and Shephard (2004) and Huang and Tauchen (2005) to test for the presence of jumps in VIX futures returns. Over the full sample period (1180 days), the number of trading days with jumps (300 days) accounts for roughly 25 percent of the sample. We also separate our full sample by the jump detection approach into two subsamples: trading days with the presence of price jumps and trading days with no jumps. A comparison between the contributions of the VIX spot and futures to price discovery in the two subsamples reveals consistent results. In addition, consistent with Simon and Campasano (2014).[7]

Although both the VIX index and VIX futures return series display excess kurtosis, the excess of the spot VIX (2516.86) is considerably larger than of the VIX futures (348.16), indicating that extreme fluctuations occur more often in the former spot VIX. The results of the augmented Dickey–Fuller unit root test indicate that all series are stationary.

4.2. VIX price discovery

Prior to exploring price discovery between the VIX and VIX futures, we conduct the Johansen cointegration and Granger causality tests. Table 3 reports the results of the Johansen maximum-eigenvalue test and trace test. The VIX index level and VIX index futures prices are cointegrated, with cointegrating rank $r = 1$; this result implies one common stochastic trend ($k = N^- r = 1$), which is consistent with the finding of Shu and Zhang (2012).

[6] Results are available upon request. We are grateful to an anonymous referee for pointing out this important issue of data selection at the optimal frequency.
[7] Results are available on request.

Table 2
Summary statistics of VIX index and VIX futures market returns.

Variables	VIX index returns	VIX futures returns	Futures basis
Mean	0.041	0.038	−0.434
Std. Dev.	92.685	44.896	2.679
Skewness	3.521	3.907	4.379
Kurtosis	2516.860	348.160	34.290
ρ	−0.105***	−0.021***	0.966***
Q (15)	2879***	105***	890,214***
ADF test	−193.800***	−396.770***	−9.957***
No. of Obs.	151043	151043	151043

Notes: The sample period runs from May 3, 2004 to August 30, 2011. ρ denotes the first-order autocorrelation coefficient; $Q(15)$ refers to the Ljung–Box test statistics for serial correlation in the series up to the fifteenth order; the augmented Dickey–Fuller (ADF) statistics test the null hypothesis that a series has a unit root, with a corresponding lag for this test of 14, according to Schwarz information criterion. The five-minute VIX index and VIX futures returns are calculated as the difference in the log price multiplied by 10,000. The futures basis is obtained by subtracting the futures price from the cash price. *** indicates significance at the 1% level.

Table 3
Johansen cointegration tests.

H_0	λ_{max}	Critical value (5% level)	λ_{trace}	Critical value (5% level)
$r \leq 0$	197.33**	11.22	198.21	12.32
$r \leq 1$	0.87	4.12	0.87	4.12
No. of Obs.	151043		151043	

Notes: This table reports the results of the Johansen cointegration tests on the VIX index and VIX futures for the full sample, with the sample period running from 3 May 2004 to 30 August 2011. The null hypothesis H_0 states that the system contains at most r cointegrating vectors, as determined by Schwarz information criterion. The conclusion of the cointegration test is, however, robust with regard to the number of lags. λ_{max} is the Johansen maximum eigenvalue test statistic, and λ_{trace} is the Johansen trace test statistic. Both tests use four lags. **indicates the rejection of the null hypothesis at the 5% level.

To address the cointegrating relation between the VIX index and VIX index futures, we estimate a bivariate VEC base model for the entire sample, at five-minute frequency:

$$\begin{aligned}\Delta P_t^S &= c^S + \alpha^S (P_{t-1}^S - P_{t-1}^F) + \sum_{i=1}^{k} \gamma_{1,i} \cdot \Delta P_{t-i}^S + \sum_{i=1}^{k} \gamma_{2,i} \cdot \Delta P_{t-i}^F + \varepsilon_t^S \\ \Delta P_t^F &= c^F + \alpha^F (P_{t-1}^S - P_{t-1}^F) + \sum_{i=1}^{k} \gamma_{3,i} \cdot \Delta P_{t-i}^S + \sum_{i=1}^{k} \gamma_{4,i} \cdot \Delta P_{t-i}^F + \varepsilon_t^F\end{aligned} \tag{7}$$

where P_t^S (P_t^F) denotes the log price of the VIX index (VIX index futures) at time t.

Following prior studies (e.g., Booth et al., 1999; Tse, 2001; Theissen, 2012)., we use the pre-specified cointegrating vector (1 −1), with α^i for the coefficients on the error correction terms of the VIX index (i = S) and VIX index futures (i = F). The models are estimated using the ordinary least squares method with Newey–West standard errors and an autoregressive lag k of 4, according to Akaike information criterion.

Table 4 reports the results of the Granger causality tests based on Eq. (7). Consistent with the bi-directional causality reported by Shu and Zhang (2012), ΔP_t^F (ΔP_t^S) Granger causes ΔP_t^S (ΔP_t^F). Although the Granger test indicates bi-directional causality between the VIX and VIX futures prices, the effect of ΔP_t^F on ΔP_t^S is more significant than the effect of ΔP_t^S on ΔP_t^F. This finding motivates us to further explore the dynamic price discovery process in the VIX and VIX futures markets.

Table 5 provides the coefficient estimates of the VEC model, information shares, and common factor component weights from Eq. (7). In this model, α^S and α^F represent the deviation from the long-run equilibrium for the VIX and VIX futures series, respectively. Martens (1998) argues that the greater the propensity for one market to follow the other market is, the larger the α coefficient will be. Hence, a smaller α (in absolute value terms) indicates an information-leading market. α^S is larger than α^F (in absolute value terms), thereby implying that VIX futures play a leading informational role in the overall process of price discovery.

Table 4
Granger causality test.

Hypothesis	F stat	p-value
H_0: ΔP_t^F does not Granger-cause ΔP_t^S	1568.39	0.00
H_0: ΔP_t^S does not Granger-cause ΔP_t^F	66.88	0.00
No. of Obs.	151043	

Note: This table reports the results of the Granger causality test on the VIX index and VIX futures for the full sample using four lags. The sample period running from May 3, 2004 to August 30, 2011.

Table 5
VEC model, information shares, and common factor component weights of the VIX index and VIX index futures.

	VEC base model		VEC model with dummies	
Variables	ΔP_t^S	ΔP_t^F	ΔP_t^S	ΔP_t^F
ΔP_{t-1}^S	−0.18***	0.02***	−0.18***	0.02***
ΔP_{t-2}^S	−0.03***	0.01***	−0.03***	0.01***
ΔP_{t-3}^S	−0.07***	0.00**	−0.07***	0.00**
ΔP_{t-4}^S	−0.10***	0.00**	−0.10***	0.00**
ΔP_{t-1}^F	0.54***	−0.03***	0.54***	−0.03***
ΔP_{t-2}^F	0.17***	−0.02***	0.17***	−0.02***
ΔP_{t-3}^F	0.10***	−0.00***	0.10***	−0.00***
ΔP_{t-4}^F	0.09***	−0.01***	0.09***	−0.01***
Z_{t-1}	−0.25***	0.07***	−0.12***	0.06***
$D_{t-1}Z_{t-1}$	–	–	−0.42***	0.03
Adj. R^2	0.09	0.01	0.09	0.01
IS^i	0.27	0.73	–	–
CC^i	0.22	0.78	–	–
${IS_1}^i$	–	–	0.35	0.65
${CC_1}^i$	–	–	0.33	0.67
${IS_2}^i$	–	–	0.09	0.91
${CC_2}^i$	–	–	0.10	0.90
No. of Obs.	151043		151043	

Notes: This table reports the VEC base model with four lags, as defined in Eq. (7), along with the VEC model with dummy variables with four lags, as defined in Eq. (8). The models are estimated using ordinary least squares with Newey–West standard errors. The autoregressive lag k of 4 is selected according to Akaike information criterion. IS^i and CC^i are the information shares and common factor component weights, respectively, of the VIX index and VIX futures calculated from the VEC base model. The sample period is from May 3, 2004 to August 30, 2011. ** and *** indicates significance at the 5% and 1% levels, respectively.

Table 5 shows that the information shares (common factor component weights) average of VIX futures in the VEC base model is 0.73 (0.78), which dominates the information shares (common factor component weights) average of the spot VIX at 0.27 (0.22). This evidence provides support for the leading informational role of VIX futures within the price discovery process.

We also employ the VEC model with dummy variables to capture the role of the futures basis in price discovery between the VIX and VIX futures. Based on the assumption in Eq. (7) that the speed of adjustment to deviations in the price levels from their long-run equilibrium relation is independent of the futures basis, we modify the VEC base model as

$$\begin{aligned}\Delta P_t^S &= c^s + \alpha_1^S(P_{t-1}^S - P_{t-1}^F) + \alpha_2^S D_{t-1}(P_{t-1}^S - P_{t-1}^F)\\ &\quad + \sum_{i=1}^{k}\gamma_{1,i}\cdot\Delta P_{t-i}^S + \sum_{i=1}^{k}\gamma_{2,i}\cdot\Delta P_{t-i}^F + \varepsilon_t^S\\ \Delta P^F &= c^F + \alpha_1^F(P_{t-1}^S - P_{t-1}^F) + \alpha_2^F D_{t-1}(P_{t-1}^S - P_{t-1}^F)\\ &\quad + \sum_{i=1}^{k}\gamma_{3,i}\cdot\Delta P_{t-i}^S + \sum_{i=1}^{k}\gamma_{4,i}\cdot\Delta P_{t-i}^F + \varepsilon_t^F\end{aligned} \tag{8}$$

where ${\alpha_1}^i$ and ${\alpha_2}^i$ denote the respective coefficients on the error correction terms of the VIX index ($i = S$) and VIX index futures ($i = F$), respectively.

The dummy variable, D_{t-1}, takes the value of 1 if the VIX futures basis, as defined in Eq. (8), is positive, and zero otherwise. ${\alpha_1}^S$ and ${\alpha_1}^F$ measure the adjustment speed of the VIX index and VIX index futures toward equilibrium in cases where the VIX futures basis is negative, and ${\alpha_2}^S$ and ${\alpha_2}^F$ measure whether the adjustment speed differs if the futures basis changes from negative to positive. We expect that ${\alpha_2}^S$ and ${\alpha_2}^F$ will have the same respective signs as ${\alpha_1}^S$ and ${\alpha_1}^F$.

Table 5 also reports the coefficient estimates, information shares, and common factor component weights of the VEC model with dummy variables, based on Equation (8). $|{\alpha_1}^S|$ is larger than $|{\alpha_1}^F|$ (i.e., $|{\alpha_1}^S| - |{\alpha_1}^F| > 0$). Similar to the results of the VEC base model, VIX futures dominate the price discovery process. Furthermore, if the futures basis is positive, the estimates of the coefficient on the error correction term ($= {\alpha_1}^i + {\alpha_2}^i$) still have the same sign and the same result; that is, $|{\alpha_1}^S + {\alpha_2}^S|$ is larger than $|{\alpha_1}^F + {\alpha_2}^F|$. However, the absolute difference between the coefficient estimates on the error correction term ($= |{\alpha_1}^S + {\alpha_2}^S| - |{\alpha_1}^F + {\alpha_2}^F|$) is greater in magnitude than $|{\alpha_1}^S| - |{\alpha_1}^F|$. This finding provides support for the notion that the VIX futures market has a positive influence on price discovery when the futures basis is positive.

Table 5 also computes the information shares and common factor component weights of the VIX and VIX futures using Eq. (8). The positive and negative futures basis, the information shares, and common factor component weights of VIX index futures are larger than those of the VIX index. The information shares (common factor component weights) of the VIX futures and VIX are 0.91 (0.90) and 0.09 (0.10), respectively, when the futures basis is positive. Comparatively, the information shares (common factor component weights) of the VIX futures and VIX are 0.65 (0.67) and 0.35 (0.33), respectively.

The use of the information share and common factor component weight approaches provides a simple and clear comparison of the contribution to price discovery for both positive and negative futures basis. Overall, our empirical results show that the VIX futures market's contribution to price discovery increases when the level of the spot VIX exceeds that of the VIX futures.

Table 6
Daily information shares and common factor component weights of the VIX index and VIX index futures.

Variables	Full sample	$Basis_t > 0$	$Basis_t < 0$
VIX Index			
Information shares	0.281	0.267	0.312
Common factor components	0.261	0.247	0.290
VIX Futures			
Information shares	0.719	0.733	0.687
Common factor components	0.739	0.752	0.710
t-statistic for IS_t^S and IS_t^F	38.320***	34.670***	17.440***
t-statistic for CC_t^S and CC_t^F	38.450***	34.880***	17.500***
No. of Obs.	1180	359	821

Notes: This table reports the averages of the daily information shares and common factor component weights for both the full sample and the subsamples, with the sample period running from May 3, 2004 to August 30, 2011. The t-statistics test the null hypotheses that the differences between IS_t^S and IS_t^F (CC_t^S and CC_t^F) is equal to zero across the different sample periods. *** indicates significance at the 1% level.

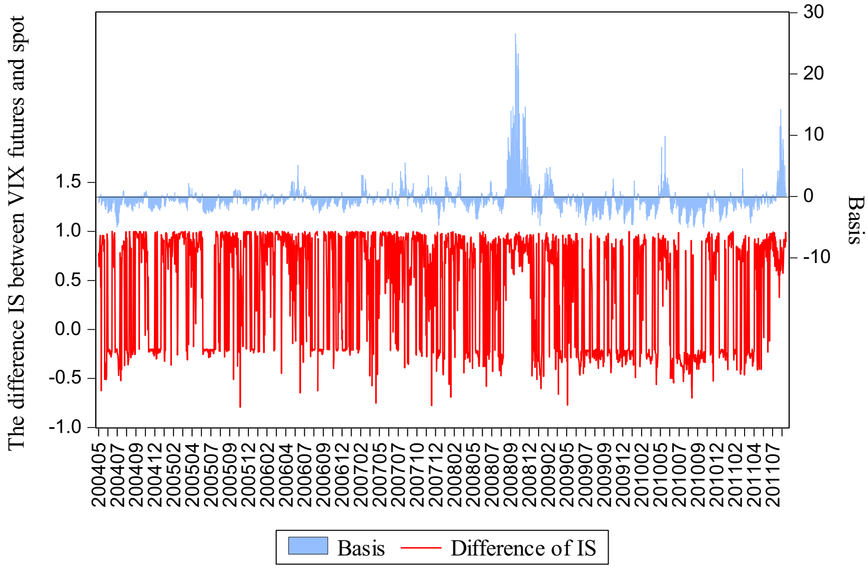

Fig. 2. Difference in information shares of VIX futures, spot, and futures basis, 2004–2011. *Notes:* The difference in information shares is defined as that of the VIX futures minus that of the VIX spot. VIX futures basis is defined as the level of the VIX index minus the price of the nearest VIX futures contract.

4.3. Daily information share and common factor component weight measures

Next we analyze time-varying price discovery between the VIX and VIX futures. We use five-minute data on the VIX and VIX futures to obtain the daily information share and common factor component weight measures to test our hypothesis on the futures market's contribution to price discovery. We divide the full sample into days with a positive and negative average futures basis. Table 6 reports the daily average of the information shares and common factor component weights of the VIX and VIX futures for the full sample and the two subsamples.

Table 6 shows that the average information shares of VIX index futures dominate those of the VIX index. For the full sample, VIX index futures (VIX index) contributes 71.9 percent (28.1 percent). The t statistic rejects the null hypothesis of zero difference in price discovery between the VIX and VIX futures, which confirms that VIX futures contribute more to price discovery than the VIX index. A comparison of the two subsamples, divided on positive and negative futures basis, shows that VIX index futures are largest (smallest) in the positive (negative) futures basis subsample. This result confirms our previous finding that the VIX futures market contributes more to price discovery when the spot VIX index exceeds VIX futures prices. The common factor component weight measure provides similar results.

Figs. 2 and 3 illustrate the difference in daily information shares and common factor component weights, respectively, between VIX futures and spot and futures basis series (compiled from the VIX index ⁻ VIX futures price).[8] The difference in information shares (common factor component weights) is defined as the information shares (common factor component weights) of VIX futures minus the information shares (common factor component weights) of the VIX spot market.

[8] We thank an anonymous referee for this suggestion to illustrate the relation over time between price discovery and the futures basis.

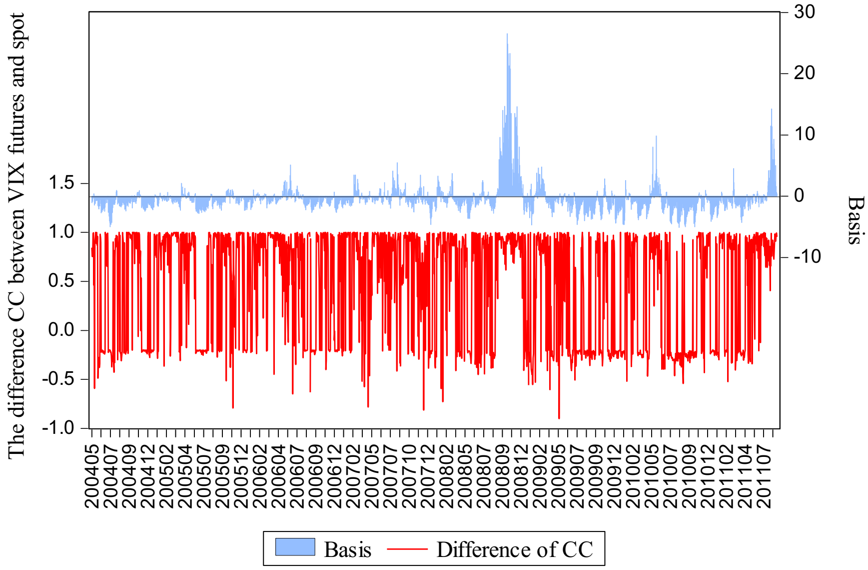

Fig. 3. Difference in common factor component weights of VIX futures, spot, and futures basis, 2004–2011. *Notes:* The difference in common factor component weights is defined as that of VIX futures minus that of VIX spot. VIX futures basis is defined as the level of the VIX index minus the price of the nearest VIX futures contract.

Fig. 2 shows that during the financial crisis period (September 2008–June 2009) the VIX index is at a much higher level than VIX futures; thus, the futures basis increased quite drastically. The difference in information shares (futures minus spot) remains at a higher level (about 0.5–0.8). These results again confirm our previous finding that a higher futures basis enhances the VIX futures market's contribution to the process of price discovery. The common factor component weight measure in Fig. 3 provides similar results.

4.4. Determinants of daily information share and common factor component weights

Prior literature focuses on the determinants of price discovery between stock index and the corresponding futures market (e.g., Roope and Zurbruegg, 2002; Covrig et al., 2004; So and Tse, 2004; Chen and Gau, 2009). The research shows that the overall process of price discovery is associated with either transaction costs or the bid–ask spread. Chen and Gau (2010) and Chang et al. (2013) examine the determinants of price discovery in the FX futures market and find significant associations with macroeconomic announcements, trading volume, bid–ask spreads, and the structure of the investors. Similarly, Mizrach and Neely (2008) and Fricke and Menkhoff (2011) investigate the determinants of price discovery between the US Treasury spot and futures markets and find that price discovery is significantly influenced by trading volume, the relative bid–ask spreads, and realized volatility.

In summary, prior research finds that price discovery between asset spot and futures prices is largely dependent on bid–ask spreads, trading volume, market conditions, and macroeconomic announcements. Theissen (2002) analyzes price discovery in floor-based and electronic exchanges using data from the German stock market and find that the contribution to price discovery is positively related to the market shares of the trading systems. Chakravarty et al. (2004) explore the determinants of price discovery between individual stock and the corresponding options and find that price discovery in the options market is significantly associated with relative trading volume, relative bid–ask spreads, and underlying volatility. Frijns et al. (2015) compare the price discovery of Canadian companies listed on the Toronto Stock Exchange (TSX) and the New York Stock Exchange (NYSE) and find that price discovery in the NYSE becomes more important on macroeconomic news announcement days. Consequently, markets with greater liquidity and lower trading costs should have an increased information share and thus should also play a more important role in the overall price discovery process. However, contrary to the results in the prior studies, the unique feature of the volatility index (i.e., the tendency to follow a mean-reversion process) may significantly affect the price discovery relation between the VIX and VIX futures prices.

The spot VIX index reflects 30-day implied volatility, whereas the corresponding VIX futures market reflects forward implied volatility (i.e., the expected volatility for the subsequent 30-day period). If behavioral bias of traders causes a temporary increase in the VIX index, then, as a result of the mean-reversion property of volatility, VIX futures prices will not increase at the same rate as the spot VIX. Thus, the futures basis is expected to play a more important role in the price discovery process.

We estimate the following regression to determine the relative contributions to price discovery made by the futures basis, bid–ask spreads, trading volume, and underlying volatility:

$$IS_t^F = \alpha + \beta \cdot X_t + \varepsilon_t \tag{9}$$

$$CC_t^F = \alpha + \beta \cdot X_t + \varepsilon_t, \tag{10}$$

Table 7
Determinants of VIX futures contributions to price discovery.

Panel A: Dependent variable: IS_t^F

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Explanatory variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	−1.15***	0.32	−1.26***	0.35	−1.25***	0.33	−0.51***	0.03	−0.51***	0.03
$Basis_t$	–	–	0.03**	0.01	0.02**	0.01	–	–	0.03***	0.01
$d(SP_t)$	3.29**	1.41	3.81***	1.46	–	–	–	–	–	–
$Dummy_t^L$	–	–	–	–	0.18**	0.06	–	–	–	–
$Dummy_t^H$	–	–	–	–	0.04	0.06	–	–	–	–
$\ln(Volume_t)$	0.06***	0.02	0.04*	0.02	0.04	0.02	–	–	–	–
$\ln(Spread_t)$	−0.04	0.07	−0.09	0.08	−0.08	0.08	–	–	–	–
News Announcements										
CPI	0.29***	0.07	0.31***	0.07	0.30*	0.17	0.25***	0.07	0.15	0.29
GDP	0.09	0.18	0.09	0.17	0.10	0.17	0.03	0.18	0.15	0.17
UMP	0.14	0.18	0.15	0.17	0.14	0.16	0.05	0.18	0.31*	0.18
Interaction effects of news dummies with the futures basis (coefficients×10)										
$CPI\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.01*	0.00
$GDP\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.02*	0.00
$UMP\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.03***	0.00
$AR(1)$	0.15***	0.04	0.17***	0.04	0.16***	0.04	0.14***	0.04	0.16***	0.03
Adj. R^2	0.03		0.05		0.05		0.02		0.05	
No. of Obs.	1180		1180		1180		1180		1180	

Panel B: Dependent variable: CC_t^F

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Explanatory variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	−0.81*	0.44	−0.93**	0.45	−0.90**	0.46	−0.57***	0.03	−0.57***	0.03
$Basis_t$	–	–	0.03***	0.01	0.02**	0.01	–	–	0.03***	0.01
$d(SP_t)$	5.22***	2.01	5.81***	2.19	–	–	–	–	–	–
$Dummy_t^L$	–	–	–	–	0.25**	0.10	–	–	–	–
$Dummy_t^H$	–	–	–	–	0.06	0.08	–	–	–	–
$\ln(Volume_t)$	0.11***	0.02	0.08*	0.04	0.07	0.05	–	–	–	–
$\ln(Spread_t)$	0.07	0.09	0.02	0.10	0.03	0.10	–	–	–	–
News announcements										
CPI	0.40***	0.08	0.43***	0.08	0.41*	0.25	0.35***	0.07	0.24	0.15
GDP	0.21	0.24	0.21	0.19	0.22	0.24	0.12	0.20	0.25	0.15
UMP	0.22	0.23	0.23	0.19	0.23	0.23	0.13	0.19	0.40***	0.13
Interaction effects of news dummies with the futures basis (coefficients×10)										
$CPI\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.01*	0.00
$GDP\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.01*	0.00
$UMP\ .\ Basis_t$	–	–	–	–	–	–	–	–	0.04**	0.00
$AR(1)$	0.12***	0.02	0.12***	0.03	0.12***	0.02	0.10***	0.03	0.11***	0.03
Adj. R^2	0.02		0.03		0.03		0.01		0.03	
No. of Obs	1180		1180		1180		1180		1180	

Notes: This table reports the regression results of the following models, $IS_t^F = \alpha + \beta \cdot X_t + \varepsilon_t$ and $CC_t^F = \alpha + \beta \cdot X_t + \varepsilon_t$. IS_t^F (CC_t^F) in Panel A (Panel B)denotes the contribution of VIX index futures to price discovery, as measured by the information share, *IS* (common factor component weight, *CC*), with the sample period running from 3 May 2004 to 30 August 2011. The explanatory variables include futures basis ($Basis_t$); the S & P 500 index (SP_t); a dummy variable ($Dummy_t^L$) that is equal to 1 on days when the S & P 500 index is below its 25th percentile, and zero otherwise; and a dummy variable ($Dummy_t^H$) that is equal to 1 on days when the S & P 500 index is above its 75th percentile, and zero otherwise. $Volume_t$ refers to the volume of VIX futures, and $Spread_t$ refers to the bid–ask spread of VIX futures. *CPI*, *GDP,* and *UMP* are dummy variables representing the consumer price index, gross domestic product, and unemployment rate, respectively; the news dummy variables take the value of 1 for news announcements on day *t*, zero otherwise. We use the Newey–West covariance estimator to adjust for the presence of heteroskedasticity and autocorrelation in the regression errors. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

where IS_t^F and CC_t^F denote the contributions of VIX index futures to price discovery measured by the information share and common factor component weight, respectively. The explanatory variables include the futures basis ($Basis_t$), the S & P 500 index (SP_t), and two dummy variables: $Dummy_t^L$ ($Dummy_t^H$) takes the value of 1 on days when the S & P 500 index is below (above) its 25th (75th) percentile, and zero otherwise.

$Volume_t$ is the trading volume in VIX futures; $Spread_t$ is the bid–ask spread in VIX futures; and CPI_t, GDP_t, and UMP_t are dummy variables for the consumption price index, gross domestic product, and the unemployment rate, respectively. The macroeconomic dummy variables take the value of 1 if a macroeconomic issue is announced on day t, and zero otherwise. We use the Newey–West covariance estimator to adjust for the presence of heteroskedasticity and autocorrelation in the regression errors. Table 7 reports the regression results based on Eqs. (9) and (10).

To the best of our knowledge, our study is the first attempt to identify the role of the futures basis in price discovery relating to VIX index futures. Panels A and B of Table 7 provides the results for the daily information shares and common factor component weights, respectively. Model 1 shows that when the futures basis is excluded, the changes in the S & P 500 index and trading volume have a significantly positive impact on the contribution of VIX futures to the price discovery process.[9] Models 2 and 3, which include the futures basis, show that it has a positive impact on the contribution of VIX futures to the price discovery process. These findings support the argument that a larger spread between VIX futures and the spot index—caused by short-term overreaction among investors to new information, which is subsequently revised in line with long-term expectations—increases the contribution that VIX futures make to price discovery. A larger short-term deviation in the spot VIX from the mean level is accompanied by a reduction in the relative contribution of the spot VIX to price discovery.

Changes in the S & P 500 index have a significantly positive effect on VIX futures price discovery (Table 7, Models 1 and 2). However, as Shu and Zhang (2012) note, the lead–lag relation between the VIX index and VIX futures is unstable and varies with the S & P 500 index. They find that although the VIX index leads VIX futures in Q1 of 2005, VIX futures lead the VIX index between Q1 and Q3 of 2008. Therefore, to examine the relation between VIX index price discovery and the S & P 500 index further, we add two dummy variables the regression models. $Dummy_t^H$ ($Dummy_t^L$) takes the value of 1 on days when the S & P 500 index is below (above) its 25th (75th) percentile, and zero otherwise. The inclusion of these dummies facilitates joint estimation of the price discovery relations for three subsamples: normal days, bull market days, and bear market days.

Model 3 in Table 7 shows that $Dummy_t^L$ has a significantly positive effect on the contribution of VIX futures to price discovery. This finding indicates that the role of VIX futures in the price discovery process is enhanced when the stock market experiences a significant decline. As Shu and Zhang (2012) argue, investors often exhibit significant overreaction to information during bear market periods, which can push the spot VIX far from VIX futures prices. More interesting, announcements relating to the CPI have a significantly positive effect on the price discovery contribution made by VIX futures. The regression coefficients of the bid–ask spread are insignificant in Models 1 to 3.

Model 4 of Table 7 examines the relation between VIX futures index price discovery and macro-news announcements. This model excludes other explanatory variables, such as bid–ask spread and trading volume. CPI announcements still have a significantly positive effect on the contribution of VIX futures to the volatility price discovery, whereas gross domestic product and the unemployment rate both generate insignificant effects. Models 5 shows that the interaction terms of three macro-news dummies with the futures basis all have a significantly positive effect on VIX futures price discovery. This result suggests that when a macroeconomic news announcement occurs, an increase in the futures basis is associated with an increase in the contribution of VIX futures prices to long-term equilibrium volatility. This phenomenon may be due to the overreaction of short-term volatility to macro-news announcements. The overreaction of short-term volatility to the announcements leads to a rise in the futures basis, further decreasing (increasing) the VIX spot (futures) contribution to long-term equilibrium volatility. Overall, our empirical results suggest that economic uncertainty related to macroeconomic information releases affects the spread between short- and long-term volatility expectations and affects the degree of price discovery in market volatility.

4.5. Price discovery in medium-term VIX futures contracts

In addition to our analysis of price discovery for the nearest-term VIX futures, we examine price discovery in medium-term contracts. Specifically, we use intraday data to obtain daily measures of the information shares and common factor component weights. We then compare time-varying price discovery in the VIX and VIX futures for different expiration periods.[10] Table 8 summarizes the results.

Models 1 to 3 of Table 8 show the information shares and common factor component weights of VIX futures for the second-, third-, and fourth-nearest contracts, respectively. The information shares (common factor component weights) of VIX futures for Models 1 to 3 are 0.605 (0.619), 0.599 (0.597), and 0.615 (0.609), respectively. In other words, as contract maturity increases, the price discovery contribution of VIX futures decreases. This finding suggests that the relatively lower liquidity of VIX futures with longer maturity dates delays the price discovery process. Table 8 also shows that the contribution to price discovery made by VIX futures contracts with medium-term maturity is still greater than that of the VIX index. This finding provides consistent support for the leading informational role of VIX futures in price discovery.

4.6. ETPs

ETPs include ETFs, exchange-traded vehicles, exchange-traded notes, and certificates. Since their initial launch in 2009, ETPs linked to the VIX index have seen remarkable growth, with the liquidity in these products currently standing at a very satisfactory

[9] We thank an anonymous referee for pointing out the covariates issue.
[10] We thank an anonymous referee for suggesting that we discuss this issue.

Table 8
Daily information shares and common factor component weights of the VIX and VIX futures with different expiration periods.

Models	Information share	Common factor component weight
Model 1		
VIX	0.395	0.381
2nd-nearest VIX futures contract	0.605	0.619
Difference test	33.40***	36.56***
Model 2		
VIX	0.401	0.403
3rd-nearest VIX futures contract	0.599	0.597
Difference test	32.75***	31.55***
Model 3		
VIX	0.385	0.391
4th-nearest VIX futures contract	0.615	0.609
Difference test	35.94***	34.32***

Notes: This table reports the averages of the daily information shares and common factor component weights based upon five-minute frequency data, with the sample period running from May 3, 2004 to August 30, 2011. The difference test reports the *t*-statistics of the null hypotheses that the differences between the VIX and VIX futures in the information shares and common factor component weights will be equal to zero. *** indicates significance at the 5% level.

level. An obvious spike in trading volume in VIX ETPs is discernible in June 2016 due to uncertainty in the lead up to the United Kingdom's withdrawal from the European Union.

Such rapid growth in the market for VIX ETPs motivates us to examine the informational role of these products using the information share and common factor component weight approaches.[11] Our empirical analysis is based on the observations of Bordonado et al. (2016) who find that the VXX (iPath S & P 500 VIX Short-Term Futures ETN) and the XIV (VelocityShares Daily Inverse VIX Short-Term ETN) have highest average volume levels among all VIX ETPs. Therefore, we use these two products for our empirical analysis. Table 9 reports the results.

Table 9 shows that, compared to the VIX, the information shares (common factor component weights) of the VXX are 11.2 percent (18.2 percent); however, when compared to the VIX futures, the information shares (common factor component weights) of the VXX decline to 8.2 percent (13.5 percent). The information shares (common factor component weights) of the VIX futures are 0.990 (0.963), compared to 0.977 (0.761) in the VIX spot index. These results confirm the informational advantage of VIX futures relative to VIX ETPs in the overall process of price discovery.

The CBOE also applies its proprietary methodology to create volatility indices based on non-US stock ETFs, such as the CBOE EFA ETF Volatility Index (Ticker: VXEFA), which measures the expected volatility of the iShares MSCI EAFE Index Fund (EFA)[12]; this measure tracks the investment results of an index of large-, medium-, and small-capitalization developed market equities, excluding those of the United States and Canada. Although prior studies on price discovery tend to focus on a single market (often the US market), volatility in any particular market is influenced not only by fluctuations in the home market but also by shocks arriving from foreign markets (Engle et al., 1990; Bekaert and Harvey, 1997; Ng, 2000; Bekaert et al., 2005; Baele, 2005). As a result, to provide insights into the nature and extent of globalization and regional integration, we extend our empirical analysis to compare price discovery in the VXEFA with that of the US VIX. Table 10 reports the results for the information share and common factor component weight approaches.

Table 10 shows that the information shares (common factor component weights) of the VXEFA are 45.9 percent (44.9 percent), compared to 54.1 percent (55.1 percent) for the VIX spot index. The information shares (common factor component weights) of the VXEFA are slightly lower at to 43.6 percent (32.0 percent), compared to 56.4 percent (68.0 percent) for the VIX spot index. Our empirical results therefore show that although the US VIX and the VXEFA both contribute to the overall process of price discovery, VIX futures provide a larger contribution.

5. Conclusion

This study uses the daily information share (Hasbrouck, 1995) and common factor component weights approaches (Gonzalo and Granger, 1995) to examine the intraday price discovery relation between the VIX and VIX futures. Our empirical results provide support for the leading informational role of VIX futures in the overall process of price discovery. The average information share (common factor component weight) in VIX futures is approximately 2.70 (2.83) times that of the spot VIX. Also, an increase in the VIX futures basis is positively related to a greater contribution of VIX futures prices to price discovery, defined as the difference between the VIX and VIX futures.

The average information share (common factor component weight) in VIX futures for a positive future basis subsample is 2.75

[11] We thank an anonymous referee for this insightful suggestion.
[12] The MSCI EAFE index is made up of equities from 21 developed countries comprising of Australia, Austria, Belgium, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland and the UK.

Table 9
Information shares and common factor component weights of the VIX index, VIX index futures, and VIX ETF.

Price discovery variables	InformationsShares	Common factor component weights
Between the VIX index and the VXX		
VIX Index	0.888	0.818
VXX	0.112	0.182
Between the VIX futures and the VXX		
VIX Futures	0.918	0.864
VXX	0.082	0.135
Between the VIX index and the XIV		
VIX Index	0.977	0.761
XIV	0.023	0.239
Between the VIX futures and the XIV		
VIX Futures	0.990	0.963
XIV	0.010	0.037

Notes: This table reports the average information shares and common factor component weights of the VIX index, VIX futures, and ETFs of the VXX (iPath S & P 500 VIX Short-Term Futures ETN) and the XIV (VelocityShares Daily Inverse VIX Short-Term ETN). The sample period for VIX futures and VXX (VIX index, VIX index, futures and XIV) is February 2, 2009 to August 30, 2011 (December 1, 2010 to August 30, 2011).

Table 10
Information shares and common factor component weights of the VIX index, VIX index futures and VXEFA.

Price discovery variables	Information shares	Common factor component weights
Between the VIX index and the VXEFA		
VIX Index	0.541	0.551
VXEFA	0.459	0.449
Between the VIX futures and the VXEFA		
VIX Futures	0.564	0.680
VXEFA	0.436	0.320

Notes: This table reports the average information shares and common factor component weights of the VIX index, VIX futures, and the VXEFA (CBOE EFA ETF Volatility Index). The sample period for the VIX index, VIX futures, and VXEFA is from January 2, 2008 to August 30, 2011.

(3.04) times that of the spot VIX. This finding shows that a higher futures basis leads to a reduction in the contribution of the spot VIX to price discovery. This result is consistent with the view that, due to the mean-reversion property of volatility, VIX futures provides more information on future volatility levels. In addition, short-term investor sentiment causes the VIX to deviate from the equilibrium price.

To the best of our knowledge, our study is the first to empirically examine intraday price discovery in the VIX and VIX futures based on Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) common factor component weight approaches. Our findings extend those of Shu and Zhang (2012) and Frijns et al. (2016), who mainly focus on a Granger causality analysis between the VIX and VIX futures. We also add to prior literature that uses measures of liquidity, such as trading volume and bid–ask spreads, by showing the important role played by the futures basis in the price discovery of market volatility.

Acknowledgements

This paper has benefited enormously from suggestions made by Professor Jules Van Binsbergen (the editor) and two anonymous reviewers. We also thank Carol Alexander, Chuang-Chang Chang, Te-Feng Chen, Robin Chou, San-Lin Chung, Bart Frijns, Yin-Feng Gau, Keng-Yu Ho, Chuan Yang Hwang, Han-Hsing Lee, Ji-Chai Lin, Yaw-Huei Wang, Robert I. Webb, K. C. John Wei, Pace Weng, Kuan Xu, Ting-Pin Wu, Sharon S. Yang, Jimmy Yang and Jin-Huei Yeh for their helpful comments and suggestions on this topic.

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