Does the Introduction of Index Futures Stabilize Stock Markets? Further Evidence from Emerging Markets

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Abstract

We examine how the introduction of index futures affects the stability of stock markets in seven emerging countries by studying the existence and the impact of positive feedback trading in both pre- and post-futures periods. Consistent with the findings in advanced markets, positive feedback traders are already prevalent before the introduction of index futures in six out of the seven markets studied. After the introduction of index futures, signs of positive feedback trading emerge in only two markets (India and Poland). In contrast to the evidence in developed markets, positive feedback traders migrate from spot to futures markets in four markets, which suggests that the introduction of index futures may destabilize some emerging stock markets. Another interesting finding is that positive feedback trading is more intense during market declines in the majority of the markets.

Keywords: emerging markets, feedback trading, stabilization, stock index futures

JEL classifications: G1; G15

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1. Introduction

Academics and practitioners continue to debate whether the introduction of index futures can disturb the essential stability of financial markets. However, no clear-cut consensus has been reached so far. Are index futures purely toxic and inevitably poisonous to stock markets? Cox (1976) suggests that the introduction of futures trading can increase market efficiency, as it can both reduce transaction costs and attract more investors. As a result, spot prices react more efficiently to higher information flows and offer investors a more precise signal, thus stabilizing both the spot and futures markets. At the same time, the existing research points out that the volatility of underlying markets can increase with more channels of information available, causing stock prices to become more volatile and destabilized and driving stock prices to diverge from their fundamental value.[1] For example, based on the theory of noise trading, proposed by Shiller et al. (1984), stock prices and investors can be influenced by an "outside" influence: social information—that is, fashions, fads, and trends. Moreover, Black (1986) formally defines irrational investors as noise traders who blindly focus on any information related to the valuation of assets. While people can use information to make prediction of futures price, noise can keep them from accurate estimation. In a further investigation of the noise theory, De Long et al. (1990) find that the release of information can stimulate noise traders to naively invest in the financial instruments concerned, moving the price of financial instruments away from their fundamental value in the short term. In fact, many critics of index futures claim that the convenience and low cost of index futures can attract more noise traders to invest in financial markets, leading those markets to inevitable destruction.

Given that the academic debate and ambiguous empirical evidence on the impact of introducing index futures are mostly based on mature markets[2], it is important to further examine whether the introduction of index futures attracts more noise traders or rational speculators to underlying spot markets in emerging markets. Recent literature show that

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[1] See Bar, Kown and Park (2004), who demonstrate a detailed study of the introduction of index futures can at least destabilize market in short-term by increasing volatility and reducing market efficiency.

[2] Related literature is summarized in the next section.

risk-seekers prefer futures markets to spot markets while risk-averters seem to be indifferent to the two markets (Lean, McAleer and Wong, 2015). However, there is no clear empirical evidence about the variation of volatility caused by index futures. In fact, most previous studies show that volatility can decrease after the introduction of index futures, but this cannot necessarily be regarded as the evidence of the stabilization of the underlying markets.[3] In this paper, we further investigate the influence of importing index futures into both spot markets and futures markets in seven emerging markets and quantify the impact of increased volatility. To do so, we adopt Sentana and Wadhwani's (1992) positive feedback model and attempt to answer the following five research questions. First, are the prices of index futures predictable? Second, can nonsynchronous trading cause market inefficiency? Third, how does autocorrelation of returns interfere with volatility and react to higher volatility after the introduction of index futures? Fourth, can the introduction of index futures truly influence the balance between spot and futures markets? Fifth, does positive feedback trading, if it exists, have a greater impact when the market is declining or growing?

We focus on emerging markets in general and the seven markets mentioned in particular for the following three other reasons. First, few studies examine the effects of introducing index futures in emerging markets. Because of the internationalization of financial markets and economic reforms, emerging markets are growing and gradually challenging the position of mature markets, attracting the attention of investors and financial analysts all over the world. The spotlight on capital markets in emerging countries can be attributed to their relatively low correlation with developed markets, allowing a reduction in portfolio risk through investing in emerging markets (Harvey, 1995). Second, our sample includes markets in Brazil, Russia, India, China, and South Africa (BRICS) as well as Turkey and Poland, as

[3] Bessembinder and Seguin (1992) indicate that predictable transaction of futures contracts can lower price volatility. Pierluigi and Laura (2002) show a specific empirical result that the introduction of index futures can reduce market volatility in Italy. Bar, Kown and Park (2004) also imply that increased volatility brought by introducing index futures can be gradually reduced in long-term. On the other hand, Bar, Kown and Park (2004), Antoniou, Koutomos and Pescetto (2011) show that index futures can cause higher volatility in markets.

they represent the biggest group of emerging markets globally.[4] By 2025 the economic scale of the BRICS countries is expected to be larger than that of the G6 (Wilson and Purushothaman, 2006). Based on data from the *World Investment Report 2015* (Nations Conference on Trade and Development, 2016), foreign direct investment (FDI) inward and outward stocks in all seven economies make up about 34% and 33%, respectively, of all the emerging markets' FDI stocks, respectively. Third, studying such a different set of emerging markets allows us to compare the findings not only between developed and emerging markets but also among individual emerging markets operating in different geographic regions (Africa, Asia, Latin America, and Europe).

This study mainly has two contributions. First, to the best of our knowledge, there is no prior work that investigates the relationship between positive feedback trading and index futures after introducing index futures on BRICS as well as Turkey and Poland. Second, unlike previous studies merely focusing on interpreting the impact of feedback trading (e.g., Koutmos and Saidi, 2001; Bohl and Siklos, 2008; Salm and Schuppli and Kuttu, 2017), this study further explores the degree of positive feedback trading.

The rest of the paper is organized as follows. Section 2 provides a literature review. Section 3 discusses the positive feedback model. Section 4 explains the dataset and presents empirical findings. Section 5 provides a discussion of the findings. Section 6 concludes the paper with some policy implications of the findings.

2. Related Literature

The prediction of stock returns through technical analysis has been controversial. For example, Cutler et al. (1990) and Koutmos (1997a) have provided empirical evidence that stock returns are autocorrelated. The possible reasons for the autocorrelation include: (1) microstructure bias, caused by overlooking "nonsynchronous" trading (Lo and Mackinlay,

[4] As a result, there has been a growing research on emerging markets in our sample. Some recent representative studies include, among others, Ankudinov et al. (2017), Będowska-Sójka (2016), Chauhan et al. (2017), Demir et al. (2016), Gupta et al. (2016), Kang et al. (2016), Li et al. (2016), Luukka et al. (2016), Mensi et al. (2016 and 2017), Sousa et al. (2017), and Xie and Qu (2016).

1990; Scholes and Williams, 1977); and (2) anticipated temporal-varying risk premium in the short term (Conrad and Kaul, 1988; Fama and French, 1988). While it is generally recognized that the nonsynchronous trading in the financial market could cause positive autocorrelation, some studies report that stock returns are negatively autocorrelated. For example, Roll (1984) finds that dealers or market makers could be compensated by what is termed as the “bid-ask spread,” which in turn causes a first-order negative autocorrelation in returns. Koutomos (1997a) finds similar results that negative autocorrelations for six mature market stock returns can be induced by positive feedback trading by investigating the relationship between conditional volatility and the incidence of autocorrelation in daily stock index returns. Recent studies (e.g., Chau, Holmes and Paudyal, 2008; Salm and Schuppli, 2010; Chau and Deesomsak, 2015; and Kuttu and Bokpin, 2017) provide further empirical evidence that there can be negative autocorrelations with the presence of positive feedback trading in both emerging and mature markets.[5]

One of the shared premises of the aforementioned papers is that autocorrelation is assumed to be time-varying. As a well-known approach to capture the time-varying nature of autocorrelation, the positive feedback model developed by Sentana and Wadhwani (1992) investigates the interaction between conditional variance and the corresponding autocorrelations in stock returns by applying an exponential-GARCH (EGARCH)-in-mean model. Furthermore, this model captures serial correlations in stock returns that become relatively high (low) when stock volatility is low (high) in the short term, suggesting that such change could be induced by the impact of positive feedback trading in markets. Campbell, Grossman, and Wang (1993) find that the trading volumes of aggregate stocks could be related to daily stock returns of individual stocks, while the trading volume could decrease the first-order daily autocorrelation. Antoniou et al. (2005) argue that this phenomenon can be attributed to stop-loss strategy used by risk aversion investors who choose to liquidate their accounts during market declines.

[5] Other empirical results of directly using autocorrelations include, among others, Sousa, Vivian and Wohar (2016) who use macroeconomic and macro-finance indicators to predict stock returns in BRICS, as well as Buncic and Moretto (2015) who use technical and fundamental variables to forecast the copper price in London Metal Exchange.

The relationship between autocorrelations and volatility has been extensively investigated in literature. Koutmos (1997b) investigates the distribution of logarithmic daily return on six Pacific Basin stock markets and shows that they are as leptokurtic as those in developed markets. This study also reports an inverse relationship between the first- and even second-order autocorrelations and volatility Bohl and Siklos (2008) find that there can be a positive relationship between negative autocorrelations inherent in positive feedback trading and volatility. Salm and Schuppli (2010) examine both large index futures markets, such as Japan (Nikkei 225) and the United States (Dow Jones), and small emerging index futures markets, such as Poland (WIG 20) and South Africa (JSE/FTSE TOP40), and report similar results as Bohl and Siklos (2008) in that volatility can be increased by negative autocorrelation caused by positive feedback trading. Chau and Deesomsak (2015) find a negative relationship between autocorrelation and volatility in the G-7 markets by using a business cycle indicator and stock market returns. Jin (2017) also provides strong support of a negative relationship between stock returns and volatility in 16 countries and explain it by leverage effects.

A recent study by Chau, Kuo, and Shi (2015) is closely related to ours. They investigate European commodity markets and show that feedback-style trading can significantly affect electricity and coal markets. Nonetheless, they point out that this kind of relationship can vary based on market regimes. They find no significant signal of positive feedback trading exists in carbon and natural gas markets, but positive feedback trading exists in coal and electricity markets. In addition, they show that positive feedback traders may chase the arbitrage opportunities based on the level of returns, and the link between volatility and return autocorrelation can be induced by market frictions and nonsynchronous trading.

As for stock markets, Antoniou, Koutmos, and Pericli (2005) investigate whether positive feedback trading can be increased in mature capital markets by introducing index futures to spot markets. Using daily index stock returns, they find that positive feedback trading has already existed in pre-futures markets, and the introduction of index futures does not stimulate positive feedback trading in spot markets. Their results further demonstrate that the introduction of index futures may attract more rational investors but not more positive feedback traders, thus helping to stabilize both the spot and the futures markets by way of increasing information flow.

Some skeptics believe that futures trading can destabilize financial markets. Although Cox (1976) argues that the low requirement and transaction costs of futures trading can attract more speculators, Ross (1989) states that futures trading can increase information flow, thus causing more volatility in spot markets. Furthermore, De Long et al. (1990) demonstrate that noise traders can inflate prices beyond the fundamental value and further state that rational speculators may “jump on the bandwagon”, where both rational traders and “noise traders” remain in the market. Antoniou and Holmes (1995) and Antoniou et al. (1998) find that the increased information flow caused by importing futures trading can increase volatility in the spot market. Bae, Kwon, and Park (2004) show that the introduction of futures and option trading in the South Korean stock market can improve local market efficiency, but it may induce significance short-term turbulence in its underlying market. Hou and Li (2014) find that the Chinese index futures market tends to destabilize the price of the underlying stock market and decreases market efficiency.

By contrast, many studies (e.g., Baldauf and Santoni, 1991; Becketti et al., 1997; Schwert, 1990; and Spyrous, 2005) find that the development of futures and option trading does not cause much market volatility and improve the market efficiency. In addition, Fortenbery and Zapata (1997), Jochum and Kodres (1998), and Nets (1995) report that the importing of futures trading does not damage the underlying asset markets. In investigating some mature capital markets, although Antoniou et al. (2005) find that the introduction of index futures causes information inflows and ultimately increase market volatility, they argue that this cannot destabilize the underlying markets because high volatility makes the market more efficient, allowing index futures to correct their underlying prices in a more timely fashion. Frijns, Gilbert, and Zwinkels (2016) find that most mutual fund managers usually perform style-based feedback trading strategy; however, less than half of them are positive feedback traders.

Given the ongoing debate and conflicting evidence, this paper further examines the effects of introducing index futures in seven emerging stock markets and compares the findings from the BRICS markets with those of two emerging European economies, Poland and Turkey.

3. Methodology

Several feedback models are used to quantify the impact of positive feedback trading. The most commonly used method, developed by Cutler et al. (1990) and Sentana and Wadhwani (1992), suggests that positive autocorrelations of short-term returns can exist. In this paper, we employ the model proposed by Sentana and Wadhwani (1992).

3.1. The Positive Feedback Model

Following Sentana and Wadhwani (1992), we assume that there are two heteroskedastic groups: positive feedback traders and speculators.[6] We can define the proportion of the shares in the market portfolio demanded by the first group as:

$$D_{1,t-1} = \gamma R_{t-1}, \qquad (1)$$

where γ is the coefficient used to measure the extent to which positive feedback traders follow price movements—that is, the extent to which they sell (buy) after prices decrease (increase). R_{t-1} is the ex-post rate of return at time (t–1), defined as {ln[$P_{(t-1)}$] – ln[$P_{(t-2)}$]}, where ln[$P_{(t-1)}$] and ln[$P_{(t-2)}$] are the natural logarithms of asset prices at time (t–1) and (t–2), respectively.

As for the second group, rational speculators are assumed to be maximizers of expected utility. Therefore, their demand for the proportion of the market portfolio can be determined as follows:

[6] Although previous studies usually regard institutional investors as rational traders, Nofsinger and Sias (1999) find that institutional investors can also engage in positive feedback trading. Meanwhile, Bange (2000) shows that individual or small investors who are usually regarded as positive feedback traders may be rational if they are willing to bear more risk with their accumulation of wealth in the stock market.

$$D_{(2,t-1)} = (E_{(t-1)}(R_t) - \alpha) / (\theta\sigma_t^2), \qquad (2)$$

where $D_{2,t-1}$ represents the partition of shares demanded by the second group at time (t–1), E_{t-1} is their expectation based on information at time (t–1) and R_t is the ex-post return at time t. Furthermore, α is the expected return of the risk-free asset, σ_t^2 is the construction for the conditional variance of returns at time t, and θ is a fixed coefficient representing the risk-aversion of speculators. $\theta\sigma_t^2$ is the risk premium required to make speculators hold their position, where $\theta > 0$. In this model, once more "smart money" users are attracted to the market after the introduction of index futures. As these risk-averse investors will demand higher risk premiums to match the increased volatility, the price of index futures should move to a new equilibrium level, thus stabilizing asset prices.

Specifically, if investors all have the same demand for the market portfolio, then the dynamic capital asset pricing model proposed by Merton (1973) may be written as: $E_{t-1}(R_t) - \alpha = \theta\sigma_t^2$.

Where θ is the coefficient for measuring the degree of risk aversion. It is largely debated whether θ is constant or time varying. Time-varying risk aversion has been addressed in extant studies, including Brandt and Wang (2003), French et al. (1987) and Palsson (1996). Following the feedback trading model specified in Antoniou et al. (2005), Koutmos (1997a), Koutmos et al. (2006), and Sentana and Wadhwani (1992), in this study, we assume a constant θ.[7] This assumption also allows us not to change the preference relation in achieving the expected value maximization that exists between smart money users and trend chasers.

Based on market equilibrium theory, that is, ($D_{1,t-1} + D_{2,t-1} = 1$), substituting Equations (1) and (2) into the above equilibrium condition, we obtain Equation (3):

[7] Bamberg and Spremann (1981), Epstein and Zin (1991), Friend and Blume (1975), Pindyck (1988), Pratt (1964), Safra and Segal (1998), Szpiro (1986), Tobin (1958), and Wolf and Pohlman (1983) have tested for a constant value of risk aversion.

$$E_{(t-1)}\ (R_t) = \alpha_0 + \theta\sigma_t^{\ 2} - \theta\gamma\sigma_t^2 R_{t-1} \qquad (3)$$

Because the indicator of positive feedback trading γ is larger than zero, the term $-\theta\gamma\sigma_t^2 R_{t-1}$ in Equation (3) shows that negative autocorrelation in returns can be caused by positive feedback trading. Furthermore, it can also be seen that autocorrelation changes are in line with conditional volatility—that is, the greater the negative autocorrelation in returns, the higher the volatility. However, through predictable returns, speculators cannot gain from positive feedback trading because it can also bring about larger volatility in the markets. As a result, speculators demand higher risk premiums in order to hold their position on shares. However, integrating with the positive feedback traders, rational speculators will also demand more shares, pushing the prices to further move away from their fundamental value and gradually causing imbalance in the market. In this situation, the underlying financial market can be destabilized or even destroyed by the introduction of the financial derivatives.

Equation (3) can easily be transformed into following regression equation with the stochastic error term, ε_t :

$$R_t = \alpha_0 + \theta\sigma_t^{\ 2} - \gamma\theta\sigma_t^2 R_{(t-1)} + \varepsilon_t . \qquad (4)$$

Equation (4) shows the relationship between negative autocorrelation and positive feedback trading. As nonsynchronous trading or market inefficiency can also induce positive feedback trading, Equation (4) can be modified as follows:

$$R_t = \alpha_0 + \theta\sigma_t^{\ 2} + \left(\varphi_0 + \varphi_1\sigma_t^2\right) R_{t-1} + \varepsilon_t \qquad (5)$$

where φ_1 is equal to $-\Upsilon\theta$. If φ_1 is statistically significant and negative, then positive feedback trading should exist. Moreover, φ_0 is used to describe the influence of market inefficiency or nonsynchronous trading on autocorrelation in returns.

3.2. GJR-GARCH Model

Bollerslev et al. (1992) demonstrate that the volatility of stock returns is conditionally heteroskedastic. Gulen and Mayhew (2000) show that the asymmetric GJR-GARCH model proposed by Glosten et al. (1993) fits better than the symmetric GARCH model. Therefore, this study employs the GJR-GARCH model, and the conditional volatility form can be specified as follows:

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{m} \zeta_j \upsilon_{jt} \right) + \sum_{j=1}^{q} \left(\alpha_j \varepsilon_{t-j}^2 + \gamma_j \mathrm{I}_{t-j} \varepsilon_{t-j}^2 \right) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 .$$

In this study, the order of ARCH (p) and GARCH (q) are 1 and 1, respectively, which means that the above equation can be simplified as follows:

$$\sigma_t^2 = \left(\omega + \alpha_1 \varepsilon_{t-1}^2 \right) + \beta_1 \sigma_{t-1}^2 + \delta \mathrm{I}_{t-1} \varepsilon_{t-1}^2 , \qquad (6)$$

where σ_t^2 represents the conditional variance of returns at time *t*, ε_{t-1} is the white noise at time *t*, and *ω*, σ_t^2 and $\beta_1$are all fixed parameters and equal to, or larger than, zero. I_{t-1} is at unity when $\varepsilon_{t-1} < 0$ or 0 otherwise. Moreover, *δ* can reflect the significant influence of the asymmetry of positive and negative residuals on conditional volatility, which shows that negative residuals can affect volatility more significantly than positive residuals.

Although numerous studies have assumed that residuals are normally distributed, they always appear much more leptokurtic and fat tailed. In order to characterize these stylized facts, we assume that the standardized residuals from the GJR-GARCH (1,1) model follow the generalized error distribution (GED), which has been widely used in finance literature to capture the fat tailness (Koutmos, 1997b; Antoniou, Koutmos and Pericli, 2005). The density function of the GED can be written as:

$$f\left(\mu_t, \sigma_t, \upsilon\right) = \frac{\upsilon}{2} \left[\Gamma\left(3/\upsilon\right)\right]^{1/2} \left[\Gamma\left(1/\upsilon\right)\right]^{-3/2} \left(1/\sigma_t\right) \exp\left(-[\Gamma\left(3/\upsilon\right)/\Gamma\left(1/\upsilon\right)]^{\upsilon/2} \mid \varepsilon_t \mid \sigma_t \mid\right), \qquad (7)$$

where Γ is the gamma function, μ_t and σ_t are the conditional mean and conditional variance at time t, respectively, and υ is the scale parameter or the degrees of freedom. Particularly when $\upsilon = 1$, the residual follows a Laplace distribution, also known as a double exponential distribution. When $\upsilon = 2$, the residual follows a normal distribution.

Given an initial value for ε_t, the parameter vector obtained by $(\alpha_0, \gamma, \varphi_0, \varphi_1, \omega, \alpha_1, \beta, \delta, \nu)$, Θ can be estimated by maximizing the log-likelihood over the data period:

$$L(\Theta) = \Sigma_{(t=1)}^{T} log(\mu_t, \sigma_t, \nu), \qquad (8)$$

where μ_t and σ_t are the conditional mean and conditional variance, respectively; and υ is the scale parameter or the degrees of freedom. Because of the highly nonlinear nature of maximum log-likelihood estimation, a numerical estimation technique must be used to estimate the parameter vector Θ. The methodology of this numerical estimation is based on Berndt et al.'s (1974) algorithm. Unlike a normal distribution, the distribution of the GED appears to be more concentrated at the peak with fat tails, thus making the parameters asymptotically efficient.

4. Data and Summary Statistics

The data used in this study include daily index returns from the following indices obtained from Datastream: CSI 300 (China), Nifty 50 (India), Bovespa (Brazil), RTS (Russia), FTSE/JSE TOP 40 (South Africa), BIST National 30 (Turkey), and Warsaw 40 (Poland). Table 1 provides the sample periods for the spot and futures markets.

Table 1 - Sample Periods of Stock Market Indices

Stock Exchange, Country	Sample Period for Spot Market and Number of Observations	Sample Period for Futures Market and Number of Observations
Shanghai, China	08/04/2005-/09/08/2016; 2873	16/04/2010-09/08/2016; 1543
Mumbai, India	23/04/1996-09/08/2016; 5295	12/06/2000-09/08/2016; 3985
Moscow, Russia	09/01/1995-09/08/2016; 5464	03/08/2008-26/07/2016; 2866
Sao Paulo, Brazil	03/01/1972-26/07/2016' 10338	14/02/1986-09/08/2016' 6634
Istanbul, Turkey	02/01/1997-09/08/2016' 4957	02/04/2005-09/08/2016; 3000
Warsaw, Poland	21/09/1998-09/08/2016' 4667	01/03/2007-09/08/2016; 2464
Johannesburg, South Africa	30/06/1995-14/12/2016; 5600	06/03/2004-14/12/2016; 2418

Table 2 shows the descriptive statistics regarding daily stock index returns in the spot markets, while Figure 1 plots the spot returns for the seven emerging markets. Table 2 shows that both the LB(5) and LB(15) statistics are significant for all index returns in all the spot markets, suggesting that temporal dependencies exist in the first moment of the distribution in all spot markets.. It is also essential to examine the higher order of temporal dependencies. In Table 2, the LB statistic for the square of index returns is provided, showing that in all the sample markets the statistic is strongly significant, as their LB(5) statistics are several times higher than their LB(5) statistics in their first-moment dependencies. This finding reveals that emerging markets, like mature markets, have autocorrelations in both the first moment and the higher moment (Antoniou et al., 2005).

Table 2 - Descriptive Statistics for Spot Markets

	Panel A: BRICS					Panel B: Emerging Europe	
	China	**India**	**Brazil**	**Russia**	**South Africa**	**Poland**	**Turkey**
μ	0.041	0.039	0.258	0.054	0.040	0.037	0.082
σ	3.399	2.341	6.143	4.943	1.742	1.283	5.876
S	-0.527	-0.191	0.179	-0.185	-0.386	-0.720	0.164
K	6.429	10.406	5.074	5.017	9.445	8.609	7.053
AD	41.586***	64.523***	88.205***	54.251***	54.507***	64.238***	56.722***
LB(5)	16.865***	21.110*	254.062***	86.363**	35.616***	108.510***	15.914***
LB(15)	48.836***	93.890**	377.001***	111.660***	53.271***	136.740***	54.040***
$LB^2(5)$	353.680***	540.020***	3343.401***	1134.603***	1334.500***	855.380***	733.260***

Notes: This table reports the sample statistics of returns for the spot markets. μ is the mean; σ is the standard deviation; S is the skewness; K is the excess kurtosis; and D is the Anderson-Darling statistic (5% critical value is 1.36/N, where N is size of sample). LB(5), LB(15) and $LB^2$15) are the Ljung–Box statistics for R_t and R_t^2, respectively, distributed as χ^2 with n degrees of freedom, where n is the amount of lags. Significance level: * 10%, ** 5%, *** 1%.

Figure 1. Returns for Spot Indices for Brazil, China, India, Poland, Russia, South Africa, and Turkey

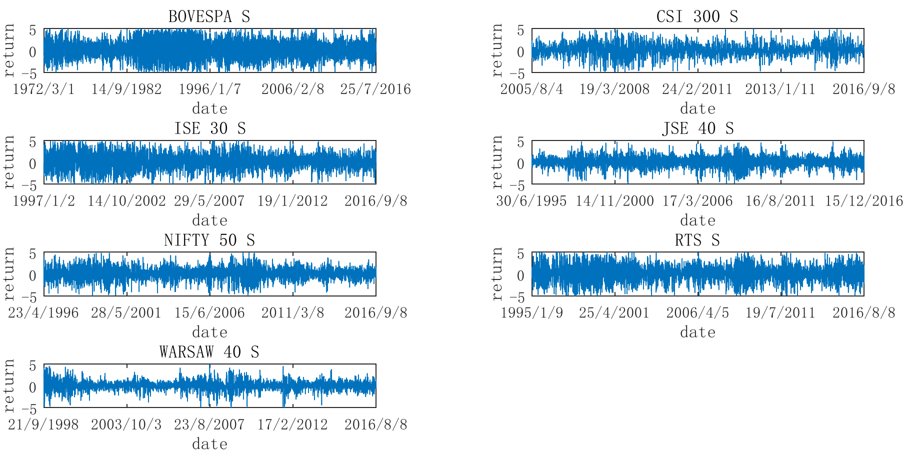


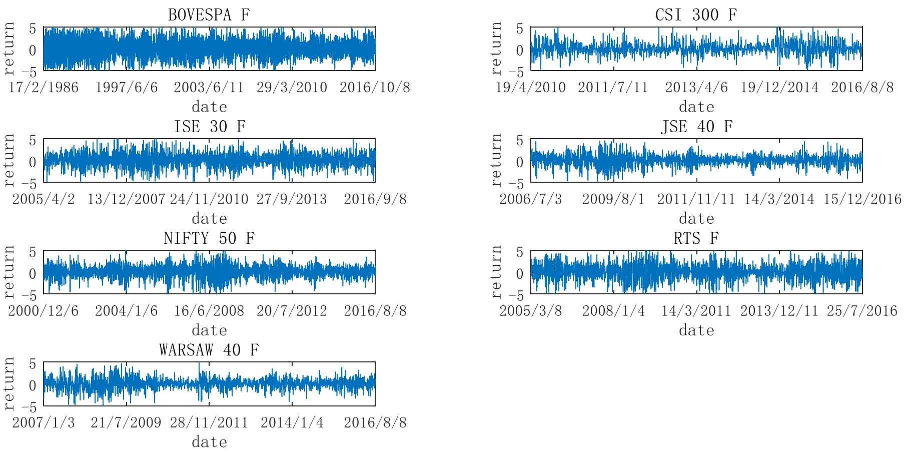
Table 3 and Figure 2 demonstrate the descriptive statistics and time series for the daily returns of futures markets. LB(5) statistics shows that temporal dependencies in the first moment of the distribution of returns are still significant in all seven markets. According to LB(15) statistics, temporal dependencies in the first moment of the distribution of returns are also presented for all markets. However, the LB statistic of squared returns—i.e., $LB^2(5)$—shows that the temporal dependencies are presented in higher moments.

Table 3 - Descriptive Statistics for Futures Markets

	Panel A: BRICS					Panel B: Emerging Europe	
	China	**Russia**	**Brazil**	**India**	**South Africa**	**Poland**	**Turkey**
μ	**-0.004**	**0.022**	**0.067**	**0.045**	**0.023**	**0.005**	**0.033**
σ	**3.073**	**4.596**	**5.983**	**2.475**	**2.034**	**1.805**	**3.257**
S	**-0.424**	**-0.136**	**-0.041**	**-0.529**	**-0.797**	**-0.636**	**-0.164**
K	**9.421**	**5.039**	**4.840**	**13.314**	**11.838**	**7.820**	**6.428**
AD	**34.608*** **	**25.044*** **	**53.351*** **	**50.232*** **	**41.217*** **	**40.489*** **	**25.030*** **
LB(5)	**35.840*** **	**9.599* **	**27.341*** **	**7.709**	**26.246*** **	**27.062*** **	**3.371**
LB(15)	**98.773*** **	**37.885*** **	**48.727*** **	**33.284*** **	**36.397*** **	**34.984*** **	**23.516* **
$LB^2(5)$	**422.220*** **	**45.342** **	**1702.208*** **	**670.102*** **	**252.641*** **	**318.110*** **	**343.130*** **

Notes: This table reports the sample statistics of returns for the futures markets. μ is the mean; σ is the standard deviation; S is the skewness; K is the excess kurtosis; and D is the Anderson-Darling statistic (5% critical value is 1.36/N, where N is size of sample). LB(5), LB(15), and $LB^2(5)$ are the Ljung–Box statistics for R_t and R_t^2, respectively, distributed as χ^2 with n degrees of freedom, where n is the amount of lags. Significance level: * 10%, ** 5%, *** 1%.

Figure 2. Returns for Index Futures for Brazil, China, India, Poland, Russia, South Africa, and Turkey



5. Empirical Findings

We report the empirical results in three parts. The first part reports the feedback model results before introducing index futures, explains the relationship between volatility and autocorrelations, and discusses whether the positive feedback trading can be more intense during market downturns. We also discuss the volatility clustering, nonsynchronous trading, and positive feedback trading in spot markets. In the second part, we report the findings after introducing the index futures and discuss whether the positive feedback trading and nonsynchronous trading are reduced in our seven markets. We also test whether the index futures can increase market efficiency, help stabilize emerging spot markets, and cause larger volatility. The third part reports the results of the diagnostic tests.

5.1. Before the Introduction of Index Futures

Table 4 shows the empirical results of the maximum likelihood estimation for the feedback model introduced in Equations (5) - (8), referred as Model I, for the period before the introduction of index futures.

To begin with, α_1, β_1 and ω, which are the coefficients describing the conditional variance series, are statistically significant at the 5% level for all markets, with the exception that ω in China's and Turkey's markets is statistically insignificant. Overall, it can be concluded that volatility clustering is highly distributed across the emerging markets.

Regarding Equation (5), Table 4 reports the parameters of the mean model—i.e., φ_0 and φ_1—which control the autocorrelation. The constant element of autocorrelation, φ_0, is statistically significant in all markets except in China and India. The estimate of φ_0 in Table 4 indicates that nonsynchronous trading can, to some extent, influence autocorrelation in index stock markets. This evidence is consistent with the results of Antoniou (2005), Fisher (1966), Lo and Mackinlay (1990), and Scholes and Williams (1977) for major mature markets, suggesting that nonsynchronous trading can have a similar impact on autocorrelation patterns in both emerging and developed spot markets.

Table 4 - Maximum Likelihood Estimation during Pre-futures Periods (Model I).

	Panel A: BRICS					Panel B: Emerging Europe	
	China	India	Brazil	Russia	South Africa	Poland	Turkey
	(04/16/2010)	(06/13/2000)	(02/14/1986)	(03/08/2000)	(03/06/2000)	(02/28/2007)	(08/18/2005)
α_0	0.241***	0.007	0.090*	0.150***	0.033	0.019	0.109***
	(0.093)	(0.102)	(0.053)	(0.011)	(0.021)	(0.027)	(0.033)
Θ	-0.006	-0.003	0.001	-0.002***	0.013	0.051	0.001
	(0.024)	(0.024)	(0.001)	(0.001)	(0.016)	(0.032)	(0.002)
φ_0	0.056	0.159	0.269***	0.133***	0.115***	0.180***	0.020***
	(0.052)	(0.135)	(0.025)	(0.010)	(0.020)	(0.036)	(0.007)
φ_1	-0.008	-0.034***	-0.002***	-0.003***	-0.013***	-0.041**	-0.001***
	(0.007)	(0.029)	(0.001)	(0.001)	(0.003)	(0.020)	(0.000)
ω	0.030	0.264	0.144***	0.155*	0.027**	0.011**	0.174
	(0.024)	(0.077)	(0.029)	(0.082)	(0.013)	(0.005)	(0.125)
α_1	0.063***	0.036	0.316***	0.216***	0.059***	0.092***	0.055
	(0.015)	(0.014)	(0.034)	(0.028)	(0.019)	(0.021)	(0.034)
β_1	0.93***	0.853***	0.735***	0.826***	0.893***	0.909***	0.907***
	(0.019)	(0.041)	(0.024)	(0.041)	(0.028)	(0.022)	(0.042)
δ	0.005	0.052***	-0.005	-0.014	0.068***	-0.015	0.065**
	(0.025)	(0.034)	(0.057)	(0.025)	(0.024)	(0.018)	(0.030)
ν	1.261***	1.112***	1.093***	0.937***	1.351***	1.312***	1.148***
	(0.081)	(0.047)	(0.129)	(0.076)	(0.057)	(0.061)	(0.131)
$\frac{(\alpha_1+\delta)}{\alpha_1}$	1.079	2.444	0.861	0.900	2.153	0.837	2.182

Notes: This table reports estimation results based on Equations (5) and (6) where pre-futures spot returns are used. Values in parentheses are the standard errors of the estimated parameters. The sample periods were obtained from Table 1. Significance level: * 10%, ** 5%, *** 1%.

$$R_t = \alpha_0 + \theta\sigma_t^2 + \left(\varphi_0 + \varphi_1\sigma_t^2\right)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \left(\omega + \alpha_1\varepsilon_{t-1}^2\right) + \beta_1\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

The order autocorrelation coefficient φ_1 is also significant in all cases with exception of China, implying that the negative autocorrelation induced by positive feedback trading can produce predictable excess returns for investors. However, this kind of mispricing, caused by positive feedback trading, cannot necessarily offer arbitrage opportunities for the "smart money" users, because the predictability caused by positive feedback trading can also raise the risk. That is, if speculators are shortsighted in terms of holding their stock index, their major concern should be about their ability to liquidate their accounts, so that they are not trapped in this risk-unadjusted price. With higher volatility, however, positive feedback trading can have a larger impact on markets, because the higher the volatility, the higher the

φ_1, inducing higher first-order negative autocorrelation. In this way, the variation in volatility in the stock index can change with the nature of autocorrelation in the returns. Looking at the estimates of φ_1 in Table 4, it can be easily inferred that there can be a positive relation between negative serial autocorrelation and volatility. This is particularly true for India and Poland in that once the value of volatility is greater than 4.676 and 4.41, positive feedback trading can easily influence their stock markets.[8] Although the coefficients for RTS and BOVESPA in India and Poland are significant, they seem to be relatively smaller than other countries.[9]

The coefficient for δ is statistically significant only for India, South Africa, and Turkey, suggesting that the conditional volatility of these markets can be modeled as an asymmetric function influenced by past volatility innovations In other words, last period's bad news can make these markets more volatile than that of good news This result is similar to the finding of Kuttu and Bokpin (2017) reported for South Africa and that of Bohl and Siklos (2008) who find no asymmetric volatility in Russia but weak asymmetry in Poland. In Equation (6), α_1 is used to measure the influence of positive residuals while $\alpha_1 + \delta$ is used to measure the influence of negative residuals on current volatility. Therefore, the ratio $\frac{(\alpha_1 + \delta)}{\alpha_1}$ is a relatively intuitive measure for testing asymmetric influence. As revealed in Table 4, the India, South Africa and Turkey index stock markets perform with the highest levels of asymmetry. These three markets, we note, that on average, are twice volatile than the other markets during market downturns.

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[8] Such a finding can be regarded as a sign of stock market collapse; for example, we observed similar conditions prior to the 1997-1998 financial crisis in Asia and the 2001 tech bubble (Bohl and Siklos, 2008). Interestingly, similar results can be found in the studies of mature markets (Antoniou et al., 2005; Bohl and Siklos, 2008).

[9] We believe that this difference for BOVESPA may be attributed to adjustments in the data for these countries. Specifically, BOVESPA has been adjusted 11 times by a factor of 100 in 1983 and by factor of 10 in 1985, 1988, 1989, 1990, 1991, 1992, 1993, 1994, and 1997. Data obtained from DataStream also show clear breaks in these adjusted points. As for RTS, the autocorrelation in Russia is constant instead of time-dependent, which is totally different from other studies in mature countries (Antoniou et al., 2005). Bohl and Siklos (2008) also show a similar result in Russia that there can be larger impact of nonsynchronous trading than that of positive feedback trading in autocorrelations.

Because of the asymmetric conditional variance, positive feedback trading is more significant during market downturns than market upturns, and this finding coincides those reported in Antoniou et al. (2005), Koutmos (1997a), Koutmos and Sadi (2001), and Sentana and Wadhwani (1992) for both emerging and mature markets. Although it is not entirely clear why positive feedback trading is more active during market declines, it may be attributed to the existence of portfolio insurance strategies. extensive application of stop-loss orders and margin trading. That is, investors using a stop-loss strategy usually sell their stocks to prevent further loss during market declines, increasing the amount of positive feedback trading. At the same time, margin trading can be another essential factor because margin accounts may be liquidated during large market declines.

In order to further investigate the period in which positive feedback trading is more intense, it is essential to add another parameter, $\varphi_2 \mid R_{t-1} \mid$ to Equation (5). We refer to Equation (10) along with Equation (6) as Model II. Here, the coefficient of R_{t-1} is given as follows:

$$\varphi_0 + \varphi_1 \sigma_t^2 + \varphi_2 \quad \text{if} \quad R_{t-1} \geq 0; \text{ or } \varphi_0 + \varphi_1 \sigma_t^2 - \varphi_2 \quad \text{if} \quad R_{t-1} < 0 \qquad (9)$$

Ceteris paribus, the new mean equation must be given as follows:

$$R_t = \alpha_0 + \theta \sigma_t^2 + \left(\varphi_0 + \varphi_1 \sigma_t^2 + \right) R_{t-1} + \varphi_2 | R_{t-1} | + \varepsilon_t \qquad (10)$$

Equation (9) shows that, for positive lagged returns with statistically significant $\varphi_2 \geq 0$, greater positive feedback trading can follow market declines. By applying Model II to the pre-futures periods of stock index markets, Table 5 shows that estimates of the coefficient φ_2 are all statistically significant only for BRICS markets, which means that positive feedback trading may occur more frequently during market declines in these countries. This evidence shows that positive feedback trading can influence emerging stock index prices in a highly volatile market. Therefore, feedback trading can have a negative influence and destabilize stock markets. However, the evidence is weak as it does not hold for the markets of Poland or Turkey.

Table 5 - Maximum Likelihood Estimation during Pre-futures Periods (Model II)

	Panel A: BRICS					Panel B: Emerging Europe	
	China	**India**	**Brazil**	**Russia**	**South Africa**	**Poland**	**Turkey**
α_0	**0.165**	**-0.021**	**0.037**	**0.103*** **	**0.046** **	**0.028**	**0.050**
	(0.081)	**(0.048)**	**(0.026)**	**(0.003)**	**(0.023)**	**(0.031)**	**(0.086)**
θ	**−0.040**	**0.027** **	**-0.002*** **	**-0.001** **	**0.021**	**0.064* **	**-0.002**
	(0.029)	**(0.013)**	**(0.001)**	**(0.001)**	**(0.015)**	**(0.034)**	**(0.012)**
φ_0	**0.004**	**0.192*** **	**0.264*** **	**0.127*** **	**0.119*** **	**0.183*** **	**0.113*** **
	(0.046)	**(0.050)**	**(0.055)**	**(0.011)**	**(0.021)**	**(0.032)**	**(0.029)**
φ_1	**-0.005**	**-0.040*** **	**-0.002*** **	**-0.002*** **	**-0.014*** **	**-0.042** **	**-0.007*** **
	(0.008)	**(0.012)**	**(0.001)**	**(0.001)**	**(0.005)**	**(0.018)**	**(0.002)**
φ_2	**0.146*** **	**-0.071*** **	**0.051*** **	**0.036*** **	**-0.033* **	**-0.035**	**0.043**
	(0.051)	**(0.018)**	**(0.011)**	**(0.001)**	**(0.018)**	**(0.037)**	**(0.035)**
ω	**0.029**	**0.312** **	**0.147**	**0.154**	**0.027** **	**0.011** **	**0.122**
	(0.025)	**(0.101)**	**(0.410)**	**(0.120)**	**(0.012)**	**(0.005)**	**(0.085)**
α_1	**0.058*** **	**0.029** **	**0.319*** **	**0.218*** **	**0.059*** **	**0.091*** **	**0.075*** **
	(0.012)	**(0.014)**	**(0.066)**	**(0.043)**	**(0.019)**	**(0.021)**	**(0.023)**
β_1	**0.933*** **	**0.835*** **	**0.733*** **	**0.825*** **	**0.893*** **	**0.908*** **	**0.901*** **
	(0.022)	**(0.038)**	**(0.025)**	**(0.035)**	**(0.027)**	**(0.022)**	**(0.031)**
δ	**0. 009**	**0.074** **	**-0.005**	**-0.015**	**0.069*** **	**-0.014**	**0.030**
	(0.026)	**(0.030)**	**(0.051)**	**(0.036)**	**(0.023)**	**(0.018)**	**(0.020)**
ν	**1.259*** **	**1.124*** **	**1.094*** **	**0.936*** **	**1.357*** **	**1.314*** **	**1.433*** **
	(0.064)	**(0.065)**	**(0.125)**	**(0.014)**	**(0.052)**	**(0.044)**	**(0.058)**

Notes: This table reports estimation results based on Equations (6) and (10) where pre-futures spot returns are used. Values in parentheses are the standard errors of the estimated parameters. The sample periods were obtained from Table 1. Significance level: * 10%, ** 5%, *** 1%.

$$R_t = \alpha_0 + \theta\sigma_t^2 + \left(\varphi_0 + \varphi_1\sigma_t^2 + \right) R_{t-1} + \varphi_2 |\ R_{t-1}| + \varepsilon_t$$

$$\sigma_t^2 = \left(\omega + \alpha_1\varepsilon_{t-1}^2\right) + \beta_1\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Table 6 - Maximum Likelihood Estimation during Post-futures Periods (Model I)

	Panel A: BRICS					Panel B: Emerging Europe	
	China	India	Brazil	Russia	South Africa	Poland	Turkey
α_0	-0.060	0.038**	0.158***	0.069*	-0.012	0.022	0.104*
	(0.083)	(0.023)	(0.004)	(0.039)	(0.026)	(0.028)	(0.059)
θ	0.040	0.011	0.001***	-0.001	0.039**	0.007	-0.150
	(0.036)	(0.011)	(0.000)	(0.010)	(0.015)	(0.022)	(0.020)
φ_0	-0.007	0.088***	0.044***	0.065***	-0.009	0.136***	0.043
	(0.049)	(0.017)	(0.054)	(0.016)	(0.025)	(0.029)	(0.027)
φ_1	0.002	-0.007*	-0.001	-0.002	0.004	-0.002**	-0.008
	(0.045)	(0.004)	(0.001)	(0.003)	(0.006)	(0.001)	(0.005)
ω	0.039*	0.065***	0.175***	0.078***	0.028***	0.059**	0.121**
	(0.021)	(0.016)	(0.042)	(0.019)	(0.008)	(0.023)	(0.049)
α_1	0.049***	0.031**	0.204***	0.034***	0.030***	0.051***	0.036***
	(0.014)	(0.016)	(0.078)	(0.011)	(0.010)	(0.019)	(0.012)
β_1	0.930***	0.861***	0.790***	0.904***	0.911***	0.829***	0.879***
	(0.019)	(0.017)	(0.016)	(0.014)	(0.013)	(0.038)	(0.030)
δ	0.007	0.147***	-0.085	0.083***	0.143***	0.139***	0.093**
	(0.020)	(0.032)	(0.078)	(0.019)	(0.020)	(0.049)	(0.032)
ν	1.154***	1.334***	1.028***	1.307***	1.754***	1.408***	1.442***
	(0.043)	(0.049)	(0.080)	(0.063)	(0.076)	(0.057)	(0.057)
t-statistics $\varphi_0^b=\varphi_0^a$	-7.264***	-55.699***	-28.542***	-31.932***	-38.731***	-9.518***	8.246***
t-statistics $\varphi_1^b=\varphi_1^a$	2.195**	-14.552***	7.071***	3.162***	25.342***	19.476***	-9.899***
t-statistics $\omega_b=\omega_a$	2.822***	-25.303***	6.073***	-9.148***	0.655	20.393***	-3.948***

Notes: This table reports estimation results based on Equations (5) and (6) where post-futures spot returns are used. Values in parentheses are the standard errors of the estimated parameters. The sample periods were obtained from Table 1. The numbers inside the parenthesis of χ^2 statistics constitute the significance level. φ_0^b represents the coefficient before the introduction of the futures index and φ_0^a represents the coefficient after the introduction of the futures index. Significance level: * 10%, ** 5%, *** 1%. The last three rows report the results of hypothesis testing for parameter changes in the post-futures period.

$$R_t = \alpha_0 + \theta\sigma_t^2 + \left(\varphi_0 + \varphi_1\sigma_t^2\right)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \left(\omega + \alpha_1\varepsilon_{t-1}^2\right) + \beta_1\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

5.2. Post-Introduction of Index Futures

We next investigate whether the introduction of index futures can make the condition of positive feedback trading better or worse. Table 6 lists the results for the feedback trading model for the post-futures periods, along with *t*-statistics for parameter changes in the post-futures period. The estimation of coefficients in the mean equation shows significant differences. Compared with the significance of φ_1 in pre-futures periods, the estimation in post-futures periods is statistically insignificant, except for India and Turkey. Even in these two countries, the estimated φ_1 in the post-futures period is significantly lower than that in the pre-futures period, changing the structure of autocorrelation before introducing index futures. This variation of autocorrelation can be either attributed to reduced market inefficiency or smaller impact of positive feedback trading.

Table 7 - Maximum Likelihood Estimation during Post-futures Periods (Model II)

	Panel A: BRICS					Panel B: Emerging Europe	
	China	**India**	**Brazil**	**Russia**	**South Africa**	**Poland**	**Turkey**
α_0	**-0.143****	**0.014**	**0.002*****	**0.081***	**-0.0174**	**0.029**	**0.102***
	(0.061)	**(0.020)**	**(0.001)**	**(0.036)**	**(0.029)**	**(0.022)**	**(0.060)**
θ	**0.010**	**-0.001**	**0.076*****	**0.004**	**0.036****	**0.014**	**-0.019**
	(0.022)	**(0.013)**	**(0.006)**	**(0.005)**	**(0.018)**	**(0.015)**	**(0.024)**
φ_0	**-0.014***	**0.010*****	**0.031*****	**0.068*****	**-0.010**	**0.140*****	**0.041***
	(0.021)	**(0.002)**	**(0.001)**	**(0.018)**	**(0.025)**	**(0.029)**	**(0.026)**
φ_1	**0.004**	**-0.006**	**0.038*****	**-0.001**	**0.004**	**-0.002**	**-0.008****
	(0.006)	**(0.004)**	**(0.002)**	**(0.001)**	**(0.007)**	**(0.008)**	**(0.003)**
φ_2	**0.128*****	**0.058*****	**0.044*****	**−0.021**	**0.010**	**-0.022**	**0.011**
	(0.016)	**(0.010)**	**(0.001)**	**(0.020)**	**(0.032)**	**(0.040)**	**(0.032)**
ω	**0.041****	**0.069*****	**0.001*****	**0.079*****	**0.027*****	**0.060*****	**0.120****
	(0.018)	**(0.017)**	**(0.000)**	**(0.026)**	**(0.009)**	**(0.023)**	**(0.056)**
α_1	**0.044*****	**0.034****	**0.401*****	**0.035*****	**-0.004**	**0.052*****	**0.036*****
	(0.015)	**(0.015)**	**(0.018)**	**(0.011)**	**(0.010)**	**(0.015)**	**(0.011)**
β_1	**0.931*****	**0.826*****	**0.785*****	**0.904*****	**0.912*****	**0.826*****	**0.880*****
	(0.014)	**(0.020)**	**(0.010)**	**(0.017)**	**(0.016)**	**(0.038)**	**(0.036)**
δ	**0.015**	**0.153*****	**-0.214*****	**0.082*****	**0.142*****	**0.141*****	**0.092****
	(0.021)	**(0.033)**	**(0.023)**	**(0.022)**	**(0.021)**	**(0.048)**	**(0.045)**
ν	**1.132*****	**1.478*****	**0.879*****	**1.310*****	**1.754*****	**1.410*****	**1.441*****
	(0.042)	**(0.064)**	**(0.041)**	**(0.041)**	**(0.065)**	**(0.050)**	**(0.062)**
t-statistics $\varphi_2^b=\varphi_2^a$	**3.368*****	**62.647*****	**-4.709*****	**-28.464*****	**11.712*****	**2.386****	**-6.748*****

Notes: This table reports estimation results based on Equations (6) and (10) where post-futures spot returns are used. Values in parentheses are the standard errors of the estimated parameters. The sample periods were obtained from Table 1. Significance level: * 10%, ** 5%, *** 1%. The last row reports the results of hypothesis testing for parameter changes in the post-futures period.

$$R_t = \alpha_0 + \theta\sigma_t^2 + \left(\varphi_0 + \varphi_1\sigma_t^2 + \right)R_{t-1} + \varphi_2 | R_{t-1}| + \varepsilon_t$$

$$\sigma_t^2 = \left(\omega + \alpha_1\varepsilon_{t-1}^2\right) + \beta_1\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

In five of the emerging countries, positive feedback trading almost disappears after the introduction of index futures. Furthermore, the coefficient of constant autocorrelation, $\varphi_{0,}$ becomes statistically insignificant, except in India, Brazil, Russia and Poland. Even for India, Brazil, Russia and Poland, φ_0 becomes less significant than that before introducing index futures. These results show that the introduction of index futures might also reduce market inefficiency and friction in India, Brazil, Russia and Poland. That is, the statistical insignificance of constant autocorrelation shows that the speed of price adjustment or informational asymmetry is improved so that nonsynchronous trading is no longer a key factor in causing market inefficiency. At the same time, the introduction of index futures both reduces the impact of positive feedback trading in the spot markets and reduces market frictions in China, South Africa and Turkey.

With the comparison of coefficients of both conditional and unconditional variance between pre- and post-futures spot markets, we can see that they generally become larger and more significant. This result can be regarded as the implication of a negative relation between volatility brought by index futures and impact of positive feedback trading. While index futures can bring more volatility to market (e.g., Bae, Kwon and Park, 2005), it can somewhat reduce the impact of positive feedback trading in spot markets.

In order to formally test whether the change in parameters that occurred in the post-futures periods is statistically significant, we set the null hypothesis for each parameter as $H_{0,1}$ φ_0^b=φ_0^a, $H_{0,2}$: φ_1^b=φ_1^a, $H_{0,3}$: ω_b=ω_a and apply t-test**,** respectively. The estimated parameters as well as t-statistics for $H_{0,1}$, $H_{0,2}$ and $H_{0,3}$ are reported in Table 6. $H_{0,1}$ and $H_{0,2}$ are rejected for all the countries, suggesting that the degree of return autocorrelation and the level of feedback trading have changed after the introduction of index futures. In particular, φ_1 captures the possibility of positive feedback trading, so its insignificance in most countries can be used to confirm that positive feedback trading is no long dominated in spot market after introducing index futures. The null hypothesis of an unchangeable unconditional variance $H_{0,3}$ is rejected, except for South Africa. Thus, the introduction of index futures can actually increase volatility to some extent in most spot markets in our sample of emerging countries. The larger volatility can induce higher autocorrelations, thus countries with larger volatility are still faced with either significant positive feedback trading or nonsynchronous trading. Further investigation of hypothesis $H_{0,2}$: $\varphi_2^b = \varphi_2^a$ in Table 7 indicates that India, Brazil, and Russia are all strongly statistically rejected, and φ_2 in these three countries is still statistically significant, except for Russia. Thus, positive feedback trading can still be more intense during market downturns after introducing index futures.

Table 8 - Maximum Likelihood Estimation for Futures Markets (Model I)

	Panel A: BRICS					Panel B: Emerging Europe	
	China	**India**	**Brazil**	**Russia**	**South Africa**	**Poland**	**Turkey**
α_0	-0.064***	0.043*	-0.001	-0.002*	-0.015***	0.029***	0.071
	(0.002)	(0.024)	(0.001)	(0.001)	(0.004)	(0.001)	(0.046)
θ	-0.090***	0.011	0.001	0.001***	0.030***	-0.005***	-0.014
	(0.010)	(0.011)	(0.001)	(0.001)	(0.008)	(0.001)	(0.012)
φ_0	-0.001	0.078***	0.002	0.001	-0.009	0.049***	0.031
	(0.001)	(0.020)	(0.003)	(0.001)	(0.023)	(0.003)	(0.026)
φ_1	-0.016***	-0.006**	-0.003***	-0.001	-0.004	-0.003***	-0.006
	(0.001)	(0.003)	(0.001)	(0.001)	(0.006)	(0.001)	(0.004)
ω	0.028**	0.062***	0.110***	0.129*	0.040***	0.015***	0.130***
	(0.012)	(0.016)	(0.028)	(0.076)	(0.016)	(0.003)	(0.048)
α_1	0.046***	0.037***	0.043**	0.062***	0.004	0.018***	0.042***
	(0.005)	(0.012)	(0.018)	(0.014)	(0.016)	(0.005)	(0.011)
β_1	0.937***	0.859***	0.905***	0.863***	0.886***	0.945***	0.872***
	(0.010)	(0.018)	(0.015)	(0.018)	(0.023)	(0.005)	(0.031)
δ	0.014	0.148***	0.127***	0.156***	0.174***	0.068***	0.095***
	(0.015)	(0.033)	(0.021)	(0.041)	(0.037)	(0.011)	(0.035)
ν	0.980***	1.426***	0.886***	0.933***	1.122***	0.943***	1.233***
	(0.029)	(0.040)	(0.069)	(0.117)	(0.067)	(0.043)	(0.053)

Notes: This table reports estimation results based on Equations (5) and (6) where index futures returns are used. Values in parentheses are the standard errors of the estimated parameters. The sample periods were obtained from Table 1. Significance level: * 10%, ** 5%, *** 1%.

$$R_t = \alpha_0 + \theta\sigma_t^2 + \left(\varphi_0 + \varphi_1\sigma_t^2\right)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \left(\omega + \alpha_1\varepsilon_{t-1}^2\right) + \beta_1\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Furthermore, the requirements are lower for entering futures markets than for spot markets; they have lower transaction costs and higher leverage benefits. Therefore, it is possible that positive feedback traders will migrate from the spot market to the futures market, making the positive feedback trading insignificant in spot markets. Table 8 shows the results of log-likelihood estimation for models using futures returns. Firstly, it can be seen that φ_0 is only statistically significant in India and Poland. That is, with the broader informational channels and increased market efficiency offered by index futures, the futures markets in Russia, South Africa, and Turkey can attract more rational investors and less positive feedback traders. In this way, information transmitted from futures market to spot market can be quick and effective, and the negative impact inherent in asymmetric information can be deviated. Secondly, the coefficient of positive feedback trading φ_1 is still statistically significant in China, India, Brazil, and Poland, even for India which is totally dominated by positive feedback trading before introducing index futures. The significance level is reduced, suggesting some negative first-order time-varying autocorrelation in futures markets, making it consistent with the view that positive feedback traders are transferred into futures markets. However, positive feedback trading does not seem to have much influence on futures markets in Russia South Africa, and Turkey, which is consistent with the studies in mature markets (Antoniou et al., 2005) and other emerging markets (Salm and Schuppli, 2010).

However, the introduction of index futures does not reduce the influence of positive feedback trading in China, India, Brazil, and Poland. This implies that index futures may still attract more positive feedback traders than speculators to implement their trend-chasing strategies to capture arbitrage opportunities caused by positive feedback trading.

Finally, the estimated scale parameter υ is below 2 and statistically significant in all seven countries, providing strong evidence that the raw return series are not normally distributed and cannot be fully attributed to temporal first-moment and second-moment dependencies.

5.3. Diagnostic Tests

In this section, we provide some diagnostic tests. First, we implement a test for residual values followed by specification tests for the conditional variance of standardized residuals. For the former, we adapt the approach of a specification test (Hausman, 1978). Given a standard regression process, $Y = \alpha X + \varepsilon$, the standardized residual, ε, should satisfy two assumptions: (1) the conditional expectation of ε should be zero, which is also called the orthogonality assumption; (2) the standardized residual, ε, should have a spherical covariance matrix, which is also called the sphericity assumption. As shown in Table 9, the conditional expectations and variance of the standardized residuals fully meet the requirements of zero mean and unit variance in all other countries except Brazil. Furthermore, the Ljung-Box statistic is used to examine the linear and nonlinear independent relationships. Table 9 shows that the standardized residuals, ε_t/σ_t, can be regarded as uncorrelated up to fifteen lags. Therefore, the standardized residuals obtained from the positive feedback model can fulfill the specification test requirements for conditional expectations.

Table 9 - Residual Based Diagnostics for Stock Index Futures

Test	$E\left(\varepsilon_t/\sigma_t\right)$	$E[(\varepsilon_t/\sigma_t)^2]$	$LB(15)$	$LB^2(15)$
Brazil	**-0.001**	**3.048**	**1.000**	**1.000**
China	**0.034**	**0.988**	**0.251**	**0.104**
India	**-0.020**	**1.001**	**0.034**	**0.913**
Poland	**-0.029**	**1.321**	**0.399**	**1.000**
Russia	**-0.009**	**1.432**	**0.857**	**1.000**
Turkey	**0.008**	**0.999**	**0.073**	**0.340**
South Africa	**-0.020**	**0.999**	**0.057**	**0.661**

Notes: $E\left(\varepsilon_t/\sigma_t\right)$ and $E[(\varepsilon_t/\sigma_t)^2]$ are the mean and the variance of the estimated standardized residuals, respectively. LB(15) and LB^2(15) are the significance levels of the Ljung-Box statistics for $E\left(\varepsilon_t/\sigma_t\right)$ and $E[(\varepsilon_t/\sigma_t)^2]$ respectively, distributed as χ^2 with degrees of freedom equal to the number of lags.

Table 10 shows the specification tests for the conditional variance of standardized residuals. We test the extent to which the feedback model captures the volatility variation using the approach proposed by Engle and Ng (1993). The Engle-Ng tests consist of four tests: (1) the sign bias test; (2) the negative size bias test; (3) the positive size bias test; and (4) the joint F test. These tests are implemented on the estimated squared standardized residuals, $(\varepsilon_t/\sigma_t)^2$, and the squared standardized residuals of the observed variables cannot be predicted as long as the feedback model is truly applicable. The first test, the sign bias test, is used to examine the asymmetric influence of positive and negative residuals on volatility not obtained from the model. The dummy variable, S, is at unity when ε_{t-1} is negative and zero otherwise. As Table 10 shows, only the test statistics for India is statistically significant, which means that negative innovations may have a larger impact on volatility than positive innovations. The negative size bias test is used to examine the influence of small and large negative innovations and calculated against a constant, α, and $S_t^{-}\varepsilon_{t-1}$, and it shows that the feedback model can successfully capture the large and small negative innovations. The third test, the positive size bias test, is used to test possible bias related to large and small positive residuals. It is calculated against a constant, α, and $(1-S_t^{-})\varepsilon_{t-1}$ and shows that the feedback model can also successfully capture the bias associated with large and small positive innovations. The last test, the joint F test, combines a constant, α, and all three variables, S, $S_t^{-}\varepsilon_{t-1}$, and $(1-S_t^{-})\varepsilon_{t-1}$. Finally, the statistical results show that the conditional variance model can fully capture the impact of innovations in China, Russia, Turkey and Poland. In summary, considering all the four tests, the results show that the feedback model does a reasonably good job in capturing the volatility variation in our sample markets.

Table 10 - Volatility Specification Tests for Stock Index Futures

Test	Sign bias test (t-test)	Negative size bias test (t-test)	Positive size bias test (t-test)	Joint F-test
Brazil	-4.085	0.326	7.218***	8.225**
China	-0.940	-0.035	-0.032	3.190
India	0.180***	-0.086	-0.150**	7.963**
Poland	-0.747	0.237	0.618	0.804
Russia	-1.216	0.250	-0.102	0.326
Turkey	0.103	-0.039	-0.160***	7.189*
South Africa	0.172*	0.098	-0.192**	10.703**

Notes: This table reports estimation results based on Equations (11), (12), (13) and (14) where index futures returns are used. All *t*-statistics refer to coefficient β in regressions (11), (12), (13) and (14). The F-statistic is from the multiple regression (14). Significance level: * 10%, ** 5%, *** 1%.

Sign bias test: $(\varepsilon_t / \sigma_t)^2 = \alpha + \beta S_t^{-} + \varepsilon_t$ (11)

Negative size bias test: $(\varepsilon_t / \sigma_t)^2 = \alpha + \beta S_t^{-}\varepsilon_{t-1} + \varepsilon_t$ (12)

Positive size bias test: $(\varepsilon_t / \sigma_t)^2 = \alpha + \beta(1\text{-}S_t^{-})\varepsilon_{t-1} + \varepsilon_t$ (13)

F test: $(\varepsilon_t / \sigma_t)^2 = \alpha + \beta_1 S_t^{-} + \beta_2 S_t^{-}\ \varepsilon_{(t-1)} + \beta(1\text{-}S_t^{-})\ \varepsilon_{t-1} + \varepsilon_t$ (14)

5.4 Summary of Findings and Discussion

In this section, we summarize our results with respect to the five questions introduced in the introduction and compare them with findings in earlier studies.

First, are the prices of index futures predictable? While positive feedback trading can cause dynamic autocorrelation in returns of index futures, nonsynchronous trading can also produce constant autocorrelation in returns. However, only a few countries show significant influence from positive feedback and nonsynchronous trading after introducing index futures. In a nutshell, the price of index futures may not be predictable in most of emerging countries.

Second, can index futures impact market inefficiency caused by nonsynchronous (index futures) trading? In most of countries, nonsynchronous trading can cause autocorrelations in asset returns before the introduction of index futures. In addition, only India, Brazil, Russia, and Poland are still affected by nonsynchronous trading, and its impact has become smaller. That is, an increase in the speed of price adjustment or a decline in informational asymmetry caused by index futures reduces the influence of nonsynchronous trading, which further improves market efficiency.

Third, how does autocorrelation of returns interfere with volatility and react to increased volatility after the introduction of index futures? Our results show that there is a positive relationship between volatility and negative autocorrelation of returns—that is, the larger the volatility, the higher the negative autocorrelation of returns, because of the existence of positive feedback trading.

Fourth, can the introduction of index futures truly influence the balance between spot and futures markets? Our findings indicate that the introduction of index futures can cause destruction for both spot and futures markets. All markets except for China are dominated by positive feedback trading before index futures are introduced. Nevertheless, the influence of positive feedback trading is still significant in two of the spot markets after the introduction of index futures, and it also has significant impact on Chinese, Indian, Polish, Brazilian and Polish futures markets. Thus, importing index futures may cause destruction in some emerging markets.

Fifth, assuming the existence of positive feedback trading, will its existence have a greater influence during market declines or market increases? We find that positive feedback trading can cause larger effects during market downturns in five of the seven markets in our sample. This finding is basically consistent with the results of previous studies on developed markets.

Another finding that is consistent with studies in mature markets is that autocorrelation caused by positive feedback trading and nonsynchronous trading declines after the introduction of index futures in emerging markets, which makes it difficult for investors to forecast the prices of index futures due to improved market efficiency. In addition, similar as the mature markets, we find that positive feedback trading has significant influence in almost all our seven emerging markets, which also indicates that the higher the volatility, the more negative are autocorrelations. Consistent with the findings of Chau, Kuo, and Shi (2015) for European commodity markets, we also find that positive feedback trading in index future markets can be more intense during a period of market turmoil. In contrast to the evidence from mature markets, we find that the introduction of index futures cannot sufficiently stabilize either spot or futures emerging markets, as feedback trading in some emerging countries still has a strong influence after index futures are introduced (see, e.g., Koutmas 1997b; Salm and Schuppli 2010).

Finally, as we mentioned earlier, the variation of autocorrelation can be interpreted by either the improvement of market efficiency or less positive feedback trading. Compared to the prevalence of positive feedback trading before introducing index futures in spot markets, there is significant reduction of positive feedback traders after the introduction of index futures. Meanwhile, four of seven emerging futures markets are still dominated by positive feedback trading with less market inefficiency. Therefore, we believe positive feedback traders are migrated from spot markets to futures markets, although the level of market friction is reduced.

6. Conclusion and Policy Implications

We have shown that emerging stock index returns can be autocorrelated with the existence of positive feedback traders. Consistent with evidence from mature markets, we have demonstrated that positive feedback traders are predominant in the spot markets before the introduction of index futures in six out of the seven emerging countries in our sample. The feedback trading becomes more prevalent during periods of market decline, making positive feedback trading highly influential by pushing the prices to diverge from their fundamental value. After the introduction of index futures, the influence of positive feedback trading in spot markets declines, while, in futures markets, this reduction is achieved only in India, Russia, South Africa and (in particular) Turkey by the migration of the positive feedback traders to futures markets. This evidence is not consistent with the findings in developed markets.

The results show that the introduction of index futures does not increase the informational channels and stabilize the price in spot markets in all our sample countries, suggesting that the impact of the introduction of index futures on the stability of the prices of stock indices in emerging markets is mixed. While the impact of introducing index futures is positive in some markets, in other markets, it attracts more noise traders to invest in the futures markets, causing informational inefficiency and volatility and destabilizing the futures markets. As we mentioned earlier, the variation of autocorrelation can be interpreted by either the improvement of market efficiency or the less positive feedback trading. Compared to the prevalence of positive feedback trading before introducing index future in spot markets, there is significant reduction of positive feedback traders after the introduction of index futures. Meanwhile, four of the seven emerging futures markets are still dominated by positive feedback trading with less market inefficiency. Therefore, we believe positive feedback traders are migrated from spot markets to future markets, although the level of market friction is reduced.

Overall, our findings suggest that policy makers in emerging countries should be cautious and do their homework before introducing stock index futures. The introduction of index futures could destabilize stock markets, especially when the markets are unregulated or have weak financial supervision. Another important implication of our findings is that policymakers emerging economies should first improve their regulatory structures and financial supervision before attempting to introduce stock index futures.

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