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What drives the off-shore futures market? Evidence from India and China[☆]

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ABSTRACT

We investigate price determinants of offshore listed derivatives of Chinese and Indian indices when the underlying is closed for trading. Using intraday data from Singapore Exchange listed index futures, we split a trading day into pre-market hours, market hours and post-market hours. In pre-market hours, USD exchange rate explains SGX futures. During market hours, the cost of carry model drives SGX futures. Post the market hours, we find that the US market explains SGX futures prices. Our findings are consistent for both India and China, suggesting that price formation in offshore listed derivatives is not speculative, rather driven by fundamentals.

1. Introduction

In recent years, there has been a stark increase in trading and volume of offshore listed derivatives of prominent emerging-market assets. Particularly, exchanges like Singapore Exchange (SGX), Chicago Mercantile Exchange, and Osaka Securities Exchange, etc. actively host derivatives of prominent Indian and Chinese indices. Among such indices, the trading volume of FTSE A50 Index Futures of China and Nifty 50 Index Futures of India (hereafter SFC and SIN respectively) are among two of the top traded equity index futures in SGX[1]. SFC tracks the FTSE China A50 index comprising the fifty largest “A” share[2] companies traded on the Shanghai (SSE) and Shenzhen exchanges (SZSE). SIN tracks the Nifty 50 index containing the fifty largest and liquid companies that trade on National Stock Exchange of India (NSE). Trading in the SGX futures offers distinct advantages especially to the foreign and institutional investors by allowing them to trade when the underlying asset is closed for trading. SGX is also set up to provide common trading hours with the US and major European markets, thus providing strategic advantages to investors. Apart from these advantages, the mandatory regulatory requirements in both China and India require foreign investors to undergo the process of registration with the

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[1] The traded volumes (in the month of December 2017) for the two contracts stand at 6,414,773 and 1,875,564 respectively. Year on year growth of the two assets were 15% and 22% respectively. All data from SGX Monthly Market Statistics December 2017 available at http://sgx.com/wps/portal/sgxweb/home/marketinfo/market_statistics.

[2] “A” shares are Renminbi denominated securities of Chinese companies listed on either the Shanghai/Shenzhen stock exchanges. They can only be traded by residents of the People's Republic of China or under the Qualified Foreign Institutional Investor (QFII), the Renminbi Qualified Foreign Institutional Investor (RQFII) rules, or via the Stock Connect schemes.

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respective regulators, a lengthy and tedious process. Further, the presence of quotas[3], restrictions on funds repatriation and minimum lock-up period on investments made in China enable SGX as an alternative trading platform for foreign investors viewing Chinese investments. In the case of India, foreign investments are not as restricted as China, yet SGX is beneficial for investors due to lower transaction costs and absence of Securities Transaction Tax.

Given that SGX futures trade even when the underlying spot market is closed makes it intriguing to understand whether price formation is speculative or driven by fundamentals, especially during off-market hours. In perfect markets, returns on futures and their underlying assets correlate contemporaneously as the cost of carry model governs this relationship. However, the presence of market imperfections commonly enables violation of the cost of carry model, thereby allowing one market to absorb information faster as documented by Stoll and Whaley (1990) and Mackinlay and Ramaswamy (1988). Consequently, a rich strand of research emerged examining the lead-lag relationships between futures markets and the underlying spot market whose findings broadly fall into three categories. The first category consist of empirical studies by Kawaller et al. (1987), Ghosh (1993), Tse (1995), Brooks et al. (2001), and Bohl et al. (2011) who document futures returns leading spot returns. The second category of studies viz., Streche (2009), Bohl et al., (2009), Cabrera et al. (2009), Chen and Gau (2009) provide evidence to the contrary suggesting spot returns lead the futures. The third category of literature includes studies like Roope and Zurbruegg (2002), Kavussanos and Nomikos (2003), and Jackline and Deo (2011) among others suggesting the presence of bidirectional causality.

A common thread across these three categories is the fact that most of the investigations on lead-lag relationships considered ‘a’ general case wherein both spot index and futures contracts trade simultaneously. However, very few papers have empirically investigated the price determinants of the offshore derivatives when the underlying market is closed for trading. Primarily studies on cross listing have focused on competition in price discovery among exchanges [see Huang, 2002, 2004a, b for instance] or price discovery in general between underlying and offshore indices. In rarer instances, studies provide empirical evidence on other issues[4]. Further, in the case of the widely traded offshore Indian and Chinese indices, the investigations on price formation in this context are few. In the case of India, Mukherjee and Mishra (2006), Seghal and Dutt (2016) and, Kotha and Bose (2016) use data from SGX traded future contracts and provide a generalized result on lead-lag relationships primarily using daily closing price data [the latter two studies suggesting spot leads the futures]. In the case of China, Guo et al. (2013) provide evidence on price formation of offshore derivatives. In their article, Guo et al. (2013) use intraday data to primarily examine price discovery contributions of SGX and China Financial Futures Exchange on the spot during common trading hours, i.e., the price impact of derivatives housed in different exchanges upon the spot.

Given this backdrop, it is evident that (a) very few papers have provided empirical evidence on the price formation of offshore listed derivatives of popular emerging market indices, (b) the few available studies have predominantly focused on price discovery during common trading hours. However, to the best of our knowledge, no study has empirically addressed an important question of “what drives the offshore futures prices when the underlying asset is closed for trading”? This provides an ideal set up to address this question using data from Indian[5] and Chinese offshore futures data. Unlike any article that has examined off shore derivatives, we use microstructure data to provide evidence of price discovery during three different time slots (a) before the underlying opens (b) during trading hours of the underlying and (c) post underlying trading hours. The rest of this paper is organized as follows: in Section 2 we hypothesize the determinants of SGX returns and provide a brief description of the SGX contracts, in Section 3 we describe the dataset used in our study, in Section 4 we describe the methodology used, we illustrate the results in Section 5 while we conclude in Section 6.

2. SGX determinants, trade timings and time windows

SGX is one of the leading exchanges in the Asian region that houses a wide portfolio of asset classes cutting across several countries (including China, India, Japan and other popular Asian indices). While individual assets of Indian market are not allowed to trade on SGX, the derivative products of Nifty index are allowed for trading. The most popular derivative products traded SGX are index futures because they allow foreign investors to take positions on Indian and Chinese markets. Therefore, the choice of variables to explain SGX listed index prices, given FIIs are the chief traders/investors has to reflect their trading information. In this context, we conjecture that global information (through FIIs) that move prices of SGX listed futures arrive through S&P 500 index as the trading hours of S&P 500 majorly overlaps with SGX futures during closure of underlying. Table 1a illustrates the trade time overlap of SIN and SFC during the trading hours of S&P 500. SFC (09:00–16:30 and 17:00–04:45 CST) trades almost during the entire period of S&P 500 index (21:00–05:00 CST). SIN (06:30–15:45 and 16:05–02:15 IST) also has considerable overlap with S&P 500 (19:30–02:30 IST). In addition to this, we also hypothesize that traders place positions on these indices based on domestic information pertaining to the specific economies. The only avenue for traders to place such information on SGX when the underlying is closed is through the

[3] Foreign investors investing in China under the QFII or RQFII scheme face quotas allocated by State Administration of Foreign Exchange (SAFE) and the investors are responsible for trading within the limits and disclosing all the required information. However, if foreign investors invest through the Stock Connect scheme they face only market wide quotas but not at the investor level.

[4] Chung and Hseu (2008) for instance provide evidence on expiration day effects using data from Taiwan futures, suggesting presence of price reversal, volatility and volume transmission from offshore listings. Frino et al. (2013) in recent times provide evidence on rejection of order flow hypothesis using SGX listed Japan and Taiwan futures.

[5] In the case of India, not only has this question not being addressed, but the only available results on cross listings are based out of low-frequency data that may not cover the relationships, especially if the divergences get readjusted in very short periods.

Table 1a
Trading period of the assets used in the study.

	Nifty	FTX	SIN	SFC	SPY	INR & CNY
	09:15–15:30	09:30–11:30 13:00–15:00	06:30–15:45 16:05–02:15	09:00–16:30 17:00–04:45	19:30–02:30	Full day
Time zone	IST	CST	IST	CST	IST	

IST, Indian standard time and CST: China standard time; CST is 2.5 hours ahead of IST.
Abbreviations: Nifty, Nifty 50 spot index; FTX, FTSE A50 index; SIN, Singapore exchange Nifty futures; SFC, Singapore exchange A50 index futures; SPY, S&P 500 index; INR, USD/INR exchange rate; CNY, USD/CNY exchange rate.

USD denominated exchange rate, as this market is available for trading throughout the day. Table 1a also provides the data pertaining to overlap between SGX indices and USD denominated exchange rates. We observe that USD/INR and USD/CNY markets are available for trade the entire day, making it possible for traders absorb the domestic information and position themselves when the underlying is closed for trading. Finally, we also hypothesize that the lagged values of SGX indices also contribute to price formation. This also helps us account for endogeneity issues in our model proposition.

In order to provide a holistic explanation of what drives offshore derivative prices, we perform our analysis during both trading and non-trading periods of the underlying assets. We define trading period as the period when the exchange (NSE, SSE and SZSE) housing the underlying asset is open. Any timing outside this period is considered as non-trading period. As SGX based indices trade before and after the market hours of the underlying, we break the non-trading period into two parts—pre-market hours (period prior to opening of underlying market) and post-market hours. We also notice a sizeable gap between the period when the underlying market is closed and when the US market opens. Therefore, we further divide the post-market hours into two, the period after underlying closes and before opening of US market and, the common trading hours with the US market. We illustrate these time windows in Table 1b.

3. Data

The primary data used in our study consists of 30-min indexed intraday prices of underlying equity spot indices and offshore derivatives. For spot data, we use prices of Nifty 50 (Nifty), FTSE China A50 (FTX) for India and China respectively. For offshore derivatives, we use SGX listed futures contracts namely SGX Nifty 50 Index futures (SIN) for India and, SGX FTSE China A50 Index Futures (SFC) for China. We also use intraday data of S&P 500 (SPY) representing the U.S. market while we use USD/INR exchange rate (INR) and USD/CNY exchange rate (CNY) as exchange rate proxies for India and China respectively. We source our data from EIKON, the database provided by Thomson Reuters. The exchange rate data for both countries is dynamically sourced by Reuters and consolidated as a database. The data period used in our study ranges from April 20, 2016–November 16, 2017.

4. Methodology

In line with our propositions, we employ an autoregressive distributed lag (ARDL) specification that is a robust method and, in a single equation setup captures the entire dynamics. Further, it offers the flexibility of assigning different lag lengths to different variables in the equation. If the variables are integrated of different order this methodology can be extended to examine the long-run relationships using the bounds testing methodology given by Pesaran et al. (1999). However, if the variables are all of I (0) the model can be estimated using the simple OLS method. In all our specifications, we estimate the standard errors and covariances of the estimates using HAC weighting matrix (Bartlett kernel, with appropriate Newey–West fixed bandwidth). For all our results, we find variance inflation factors (VIFs) for the regressors to be less than 10 indicating absence of any multicollinearity issues.

We compute the continuously compounded returns ($\ln(p_t/p_{t-1})$) using close-to-close prices of successive 30-min intervals for all the regressors in the equation below:

$$r_{F,t} = a + \sum_{k=0}^{q} \beta_k r_{s,\, t-k} + \sum_{j=1}^{p} \gamma_j r_{F,t-j} + \epsilon_{F,t} \tag{1}$$

Table 1b
Time windows used in the study.

	Pre market	Market hours	Post market (US market closed)	Post market (US market open)
SIN	07:30–09:00	09:15–15:45	17:30–19:30	19:30–23:30
Time Zone	IST	IST	IST	IST
SFC	–	09:30–11:00 13:00–15:00	15:00–22:30	22:00–02:00
Time zone	–	CST	CST	CST

where $r_{F,t}$ is the thirty-minute SGX future returns; $r_{s,t}$ represents the returns of the independent variables and $\varepsilon_{F,t}$ representing error term is unobserved zero mean white noise. As we use returns computed at 30-min interval closing prices, we ignore the first observation in a given window in line with propositions of several studies using microstructure data. We initially estimate the model with three lags of the regressors and sequentially eliminate the regressors that are not statistically significant at 5% level of significance. We retain and document results of the estimations that improve at least two of the three information criteria (AIC, SBC and HQC). A statistically significant slope coefficient (βs and/or γs) in the above equation implies that SGX future returns are not purely speculative, but driven by fundamental information. Finally, if the SGX future movements are purely random in nature none of the regressors would be statistically significant.

ARDL models capture the determinants of the SGX future returns as well as return spillovers. We also attempt to examine the volatility spillovers amongst SGX futures, S&P 500 and USD exchange rates using a multivariate GARCH (MGARCH) framework–the BEKK model (Baba et al., 1990 and, Engle and Kroner (1995)) which ensures positive semi-definiteness by working with quadratic forms. The BEKK model estimation involves two stages starting with the estimation of the mean equation defined as:

$$\boldsymbol{Y}_t = \mathrm{K} + \Gamma \boldsymbol{Y}_{t-1} + \epsilon_t \tag{2}$$

$$\epsilon_t | I_{t-1} \sim N(0, \boldsymbol{H}_t)$$

where $\mathbf{Y_t}$ is a 3×1 vector of thirty-minute interval returns at time *t;* $\boldsymbol{K}$ is a 3×1 vector of constant terms; $\boldsymbol{\Gamma}$ is a 3×3 vector of coefficients on lagged terms of the returns. ε_t is a 3×1 vector of random uncorrelated error terms that is multivariate normally distributed (I_{t-1} denoting the information set at time *t-1*) and $\boldsymbol{H_t}$ is the corresponding 3×3 conditional variance-covariance matrix. The second stage involves specifying the conditional variance-covariance equation $\mathrm{H_t}$. In the BEKK representation the covariance structure is defined as under:

$$\boldsymbol{H_t} = \boldsymbol{C'}_0 \boldsymbol{C}_0 + \boldsymbol{A'}(\epsilon_{t-1}\epsilon'_{(t-1)})\boldsymbol{A} + \boldsymbol{B'}\boldsymbol{H}_{(t-1)}\boldsymbol{B}$$

where A and B are parameter matrices and $\mathbf{C_0}$ is restricted to be an upper triangular matrix of constant terms. The diagonal elements of matrices A and B measures the effects of own past shocks and past volatility of a given market on its conditional variance and the off-diagonal elements measure the volatility spillovers. We estimate the BEKK system using maximum likelihood method and the loglikelihood function is given as:

$$L(\theta) = -\frac{T.\,N}{2} log 2\pi - \frac{1}{2} \sum_{t=1}^{T} (log|\boldsymbol{H_t}| + \epsilon'_t \boldsymbol{H}_t^{-1} \epsilon_t)$$

where θ denotes all the unknown parameters to be estimated and *N* is the number of assets (in this study N = 3) and *T* is the number of observations.

5. Results

We begin with the summary statistics and unit root tests for all our variables, presented in Tables 2 and 3. We find all variables to have an almost zero mean while volatilities of spot indices are more than that of futures and exchange rates. All the series are leptokurtic, a characteristic we expect with high frequency data. Results from Table 3 strongly indicate that all the returns variables used in our study are stationary, therefore enabling us to use OLS estimations for Eq. (1).

5.1. Pre-market hours

We begin our narration of what drives the prices of offshore futures beginning with the pre-market trading hours. During the pre-market hours, when the underlying is closed for trading, we attempt to explain the price movements of the offshore futures using USD

Table 2
Summary statistics.

	SIN	SPY	INR	SFC	CNY	Nifty	FTX
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Median	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	−0.0162	−0.0232	−0.0041	−0.0103	−0.0034	−0.0165	−0.0101
Min	0.0100	0.0155	0.0076	0.0125	0.0016	0.0086	0.0134
Standard deviation	0.0012	0.0018	0.0005	0.0014	0.0002	0.0014	0.0019
Skew	−0.7382	−0.7540	0.9858	0.1316	−1.2845	−0.6639	0.2306
excess Kurtosis	10.4140	24.6730	19.0930	8.5617	16.9820	8.7581	4.3023
J–B statistic	42,008.70***	58,097.30***	141,336.00***	21,546.70***	51,180.20***	14,032.70***	2249.85*,**
N	9114	2282	9114	7048	4164	4292	2884

All results from Tables 2–10 are for the return series of the variables.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Table 3
Unit root tests.

	SIN	SPY	INR	SFC	CNY	Nifty	FTX
ADF test statistic	−46.08***	−10.80***	−31.30***	−19.75***	−20.24***	−14.50***	−16.46***
PP test statistic	−95.62***	−48.85***	−94.77***	−80.64***	−64.47***	−64.21***	−50.60***
KPSS test statistic	0.0391	0.0494	0.1458	0.2152	0.1702	0.0521	0.3673

*** Significant at 1% for ADF and PP tests; H0, There is a unit root for the series and Ha, There is no unit root for the series; For KPSS test H0, The

Table 4
Pre-market regression analysis for India (Response variable: SIN_t).

07:30–09:00 IST	Coefficient	*t*-statistic
Const	0	−0.51
INR_t	−0.31**	−2.13
INR_{t-1}	0.02	0.34
SIN_{t-1}	0.11	1.68
Adjusted R^2	4%	
F statistic	2.46*	

** Significant at 10%; Test statistics are based on heteroskedasticity and Autocorrelation (HAC) corrected standard errors

exchange rate as the explanatory variable using Eq. (1). However, in the case of China we note that the interval between opening of SGX future and the underlying spot market is only 30 min. As we have only one 30-min pre-market observation, we do not test this hypothesis for China and document only the India result. We present the results in Table 4. From the results, we observe that during the non-trading hours prior to the opening of NSE, there is presence of contemporaneous relationship between SIN returns and INR returns and no evidence of causal relationship between the variables.

5.2. Market hours

Next, we repeat the analysis using Eq. (1) during the market hours of NSE, SSE and SZSE. We illustrate the results in Tables 5 and 6. Firstly, we find strong contemporaneous association between SIN and the underlying spot index. We find this relationship highly significant with a slope coefficient almost equal to 1. Secondly, we also document the presence of strong bi-directional causality between SIN and Nifty. The first lag of both Nifty and SIN are statistically significant. Likewise, when we reverse the equation by attempting to model Nifty as the response variable, we find similar results the first lags of SIN and Nifty explaining Nifty spot. Thus, we find the presence of bi-directional causality between SIN and Nifty[6]. Similar to India results, we find SFC to have a significant contemporaneous relationship and feedback with its underlying asset. We find strong bi-directional causality between the spot and SFC with a high adjusted R^2 of 81% strengthening the cost of carry model during market hours. With these results, we document that during market hours, the prices of SGX traded offshore index futures of India and China are significantly explained by the contemporaneous prices of the underlying spot. We also document presence of bi-directional causality between the spot and offshore futures during market hours.

5.3. Post market hours–before opening of US markets

Next, we estimate model (1) after the closure of Indian and Chinese markets. Firstly, we estimate the regression with exchange rate as the explanatory variable. We explore this because there is a time lag between closure of underlying market and opening of US markets. Therefore, during this period the only traded asset that may bear informational influence is the exchange rate. We do this for both Indian and Chinese markets, results described in Tables 7 and 8. As with the results for the pre-market hours of NSE, we observe presence of contemporaneous relationship between INR and SIN. Further the thirty-minute lag of SIN is statistically significant. When we analyze causality in the reverse direction (Panel B), we observe that only SIN is statistically significant. We document presence of contemporaneous relationship between SIN and INR and uni-directional causality from SIN to INR. This is an indication that the price movements of SIN during this period are not purely speculative partially explained by movements in the exchange rate. For China, we find that only past values of SFC are statistically significant and CNY does not statistically explain SFC. Unlike the Indian market, where the exchange rate explains SGX derivative when spot and US markets are closed, the Chinese exchange rate has no impact on SFC. The Chinese currency is a pegged currency (unlike INR) and not fully convertible, and in general traded lesser compared to Indian currency. Therefore, it is not surprising for us to find CNY to be insignificant in explaining SFC returns. During market close and before US market opening, SFC is explained merely by its own past than by the CNY.

[6] The adjusted R^2 for both the models is around 91%, giving credence to the applicability of the cost-of-carry model.

Table 5
Market hours regression analysis for India.

09:15–15:30 IST					
Panel A (Response variable: SIN_t)			Panel B (Response variable: $Nifty_t$)		
	Coefficient	*t*-statistic		Coefficient	*t*-statistic
Const	0.0001***	9.36	const	−0.0001***	−9.46
$Nifty_t$	0.9985***	135.91	SIN_t	0.9121***	108.66
$Nifty_{t-1}$	0.1698***	10.56	SIN_{t-1}	0.1784***	12.29
SIN_{t-1}	−0.1782***	−11.62	$Nifty_{t-1}$	−0.1688***	−10.94
Adjusted R^2	91%		Adjusted R^2	91%	
F statistic	6282.08		*F* statistic	3933.31	

*** Significant at 1%; Test statistics are based on HAC corrected standard errors.

Table 6
Market hours regression analysis for China.

09:30–15:00 CST excluding 11:00–13:00 lunch break					
Panel A (Response variable: FTX_t)			Panel B (Response variable: SFC_t)		
	Coefficient	*t*-statistic		Coefficient	*t*-statistic
Const	0.0001***	5.47	Const	−0.0001***	−4.93
SFC_t	0.8555***	56.13	FTX_t	0.9496***	81.68
SFC_{t-1}	0.1011***	4.69	FTX_{t-1}	0.1297***	6.18
FTX_{t-1}	−0.1090***	−5.55	SFC_{t-1}	−0.1072***	−4.6
Adjusted R^2	81%		Adjusted R^2	81%	
F statistic	1055.44***		*F* statistic	2234.69***	

*** Significant at 1%; Test statistics are based on HAC corrected standard errors.

Table 7
Post market hours regression analysis for India.

16:05 to 19:30 IST					
Panel A (Response variable: SIN_t)			Panel B (Response variable: INR_t)		
	Coefficient	t-statistic		Coefficient	*t*-statistic
Const	0	0.56	const	0.0000**	−2.5
INR_t	−0.2146***	−4.5	SIN_t	−0.0818***	−4.87
SIN_{t-1}	−0.0822***	−2.78			
Adjusted R^2	2%	Adjusted R^2	2%		
F statistic	14.74***	*F* statistic	23.67***		

*** Significant at 1%.
** Significant at 5%; Test statistics are based on HAC corrected standard errors.

Table 8
Post market hours regression analysis for China (Response variable: SFC_t).

17:00–22:30 CST		
	Coefficient	*t*-statistic
Const	0	1.97
CNY_t	0.0266	0.33
CNY_{t-1}	−0.0504	−0.9
SFC_{t-1}	−0.0858***	−4.15
Adjusted R^2	1%	
F statistic	6.31***	

*** Significant at 1%; Test statistics are based on HAC corrected standard errors.

5.4. Post market hours–when US market is open

Lastly, we examine the offshore derivative determinants by estimating model (1) by including SPY as an additional independent variable during post market hours. We choose this because of the long overlap between SPY with SIN and SFC and also because of empirical evidence on integration of emerging markets with developed markets [apart from those studies that are already mentioned in the introduction section Mun and Brooks (2012), Syriopoulos et al. (2015) inter alia], especially the US market. In the absence of trading in the underlying asset, we expect the possibility of US market index forming the basis for trading in SGX futures. We summarize these results in Table 9 (Panel A for India and Panel B for China). First, we note the presence of considerable association in

Table 9
Post market hours regression analysis along with US for India and China.

19:30–23:30 IST Panel A (Response variable: SIN_t)			22:00–02:00 CST Panel B (Response variable: SFC_t)		
	Coefficient	*t*-statistic		*Coefficient*	*t*-statistic
Const	0	0.4	Const	0	0.81
SPY_t	0.2492***	5.02	SPY_t	0.2194***	5.63
SPY_{t-1}	0.0602***	3.9			
INR_t	−0.3082***	−4.33			
SIN_{t-1}	−0.1177***	−5.66			
Adjusted R^2	22%	Adjusted R^2	16%		
F statistic	39.51***	*F* statistic	31.73***		

*** Significant at 1%; Test statistics are based on HAC corrected standard errors.

terms of both contemporaneous and 30-min lagged returns of SIN and SPY. We find adjusted R^2 increasing to 22% implying significant explanatory power of SPY on offshore futures. Further, it is evident that INR retains its influence on the SIN returns. When the underlying asset is closed for trading (in this case Nifty index), trading in SGX futures is not speculative. A fifth of the variations of SIN is explained by global and India specific factors proxied by SPY and INR exchange rate. Further, we also observe presence of negative coefficient for SIN lagged variable. This result is significant because it potentially symbolizes mean reversion in the futures price movements. Therefore, we conclude that the SIN returns are not formed randomly, rather can be attributed to both trading in itself and as adjustment to the global and India specific information arrivals. We also replicate the Indian result based on SPY with Chinese data (Panel B). Similar to India result, we find that SPY has a statistically significant contemporaneous relationship with SFC returns. Further, the thirty-minute lagged SPY returns are also significant in explaining the price movements of SFC. This reinforces the fact that the US market acts as a cue not only to the emerging spot markets as established in literature, but also to the derivative contracts traded on offshore exchanges, particularly when the spot market is closed for trading. We prove this with both Indian and Chinese datasets. All the inferences from the above OLS estimations are robust as the test statistics are computed using the HAC consistent estimators and variance inflations factors (VIFs) of all the variables in all the models less than 10 indicating absence of any multicollinearity problems.

5.5. Volatility spillovers

To complete our narration on off shore derivatives and information flow, we finally present the results of volatility spill over using MGARCH BEKK (1, 1) model, results presented in Table 10. We do this estimation for both Indian and Chinese data. LB statistics for the 6th order in standardized residuals and squared standardized residuals show that there is no serial dependence in the residuals (at

Table 10
BEKK (1, 1) MGARCH results for India and China.

	Variables: SPY, SIN and INR (T = 2282 observations)			Variables: SPY, SFC and CNY(T = 583 observations)		
	Co-eff	Asy SE	*t*-statistic	Co-eff	Asy SE	*t*-statistic
A(1,1)	0.0962**	0.0441	2.18	0.1508***	0.0394	3.83
A(1,2)	−0.0083	0.0564	−0.15	−0.0471**	0.0219	−2.15
A(1,3)	−0.0171*	0.0097	−1.77	−0.0040	0.0082	−0.48
A(2,1)	0.0655	0.1098	0.60	0.0429	0.1050	0.41
A(2,2)	0.2327***	0.0575	4.05	0.3968***	0.1387	2.86
A(2,3)	0.0272*	0.0139	1.96	0.0817	0.0504	1.62
A(3,1)	0.2427**	0.1196	2.03	−0.0488	0.2189	−0.22
A(3,2)	−0.0342	0.1197	−0.29	0.1933	0.1628	1.19
A(3,3)	0.2244**	0.0923	2.43	0.3217***	0.0957	3.36
B(1,1)	0.9828***	0.0113	86.68	0.9800***	0.0059	166.70
B(1,2)	−0.0041	0.0167	−0.25	0.0072	0.0063	1.14
B(1,3)	0.0015	0.0015	1.04	−0.0006	0.0025	−0.23
B(2,1)	0.0102	0.0417	0.24	−0.0083	0.0570	−0.15
B(2,2)	0.9550***	0.0142	67.26	0.8948***	0.0813	11.01
B(2,3)	−0.0047	0.0064	−0.74	−0.0280	0.0316	−0.89
B(3,1)	−0.1107*	0.0627	−1.77	−0.0534	0.1357	−0.39
B(3,2)	−0.0047	0.0597	−0.08	−0.2761	0.1754	−1.57
B(3,3)	0.9528***	0.0478	19.92	0.8684***	0.0800	10.86

Variables are indexed as (1) S&P 500; (2) SIN / SFC; and (3) INR /CNY.
A is the matrix of ARCH coefficients and **B** is the matrix of GARCH coefficients respectively, A(1,2) represents element a_{12} in matrix **A** and it represents the cross-market effects of shock spillover while B(1,2) denotes the cross effect of volatility spillover.

*** significant at 1%.
** Significant at 5%.
* Significant at 10%.

1% level of significance) indicating the appropriateness of the fitted variance–covariance equation by the BEKK model. The terms A (*i, j*) and B (*i, j*) help to examine the short-term and long-term volatility spill overs respectively from *i*th market to the *j*th market. For the case of $i = j$, the term captures the ARCH and GARCH effects respectively. From the results we note that the GARCH parameter, a measure of long-term volatility persistence is statistically significant across all the three equations, with SPY showing the highest amount of persistence followed by SIN and then INR. We find evidence of bi-directional shock transmission between SPY and INR exchange rates as the pair of A(1,3) and A(3,1) are statistically significant. The significant A(2,3) term indicates unidirectional shock spillover from SIN to INR. This finding is consistent with the returns spillover observed between SIN and INR. With reference to the MGARCH estimation for the SFC shows that there is only a shock spillover from SFC to SPY as the term A(1,2) is statistically significant at 5% significance. Apart from this, none of the cross-market terms are statistically significant.

The above analysis leads us to summarize that when the underlying spot markets are open the offshore future contracts are contemporaneously associated with the underlying and there is a bi-directional causality. When the spot markets close for trading then the US market wields considerable influence on the offshore futures returns. This could possibly due to the actions of the foreign institutional investors who might be taking new/offsetting positions on emerging markets possibly based on information arrivals. However, when both spot and the US market are closed then the offshore futures returns are explained by the exchange rates especially if the currencies are partially convertible like the INR but we do not find any relationship between USD/CNY exchange rate and SFC potentially due to currency pegging. Therefore, trading in CNY is relatively less compared to that of INR throughout the day. Thus, our study is one of the first to provide insight answering the important question—'what determines offshore listed derivative prices when the underlying markets are closed'?

6. Conclusions

Our study is one of the first to empirically document the price discovery of offshore listed SGX based index futures of India and China especially when the underlying market is closed for trading. Unlike other studies, we systematically investigate whether SGX based futures prices are formed randomly or through information flow. From our analysis, we arrive at several important conclusions. Firstly, during the period before Indian market opens (early morning hours of IST) the offshore prices are primarily driven by the exchange rate. Secondly, during the period when underlying is open, there is information transfer between underlying and offshore derivative in both directions, for both India and China. Thirdly, the period after Indian market closes and before US market opens, price movements of SIN are majorly explained by INR. However, we find this relationship to be insignificant for China mainly due to the structural issues of the exchange rate. Finally, once the US market opens, both SPY and the exchange rate significantly explain price movements of SIN. For China, we find that only SPY is crucial in explaining SFC returns.

The results of our study imply the fact that the offshore derivatives act as a proxy for global investors in the Indian and Chinese markets to transfer their information as trades. In the absence of the underlying asset, this information arrives through either country specific information (exchange rate), or global information (US market). The information arriving from these markets is gradually transferred back and forth to the underlying when the underlying opens. Contrary to popular belief, the offshore derivatives are not speculative assets, but act as one of the crucial assets that transmit the impact of global information to the underlying asset and come in handy for the foreign investors in hedging and trading strategies especially when the underlying markets are closed for trading.

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