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US economic policy uncertainty and co-movements between Chinese and US stock markets

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ABSTRACT

This paper investigates the impact of innovations in US economic policy uncertainty on the co-movements of China's A/B stock markets with the US stock market. We show that it is the absolute changes in the US economic policy uncertainty index that have a negative impact on the co-movements. The finding is robust to the asymmetric effects of non-policy-uncertainty shocks, to a break in the correlation structure, and to the four Chinese A/B stock markets investigated. Our results provide the first evidence regarding how stock market correlations are driven by policy-related uncertainty shocks in the international context.

1. Introduction

Does economic policy uncertainty (EPU) in the US matter for China's stock markets? In the present study, we approach this general question by investigating specifically the impact of US EPU innovations on the co-movements between the Chinese and the US stock market. Our study is motivated by the following considerations.

First, there is growing interest in studying the link between economic policy uncertainty and financial risk management. In a recent review article, Hammoudeh and McAleer (2015, page 2) note that “research papers in financial risk management and economic policy uncertainty are among the most widely cited, downloaded and viewed articles in finance and financial economics”. Overall, the twenty-two studies reviewed therein have demonstrated that economic policy uncertainty does confound market participants and policy-makers, in terms of financial risk. However, the findings provided by these research endeavours are mainly concerned with how US EPU shocks influence the European economies or how Chinese EPU shocks affect the Greater China economy. No studies have looked at the impact of US EPU shocks on the Chinese stock markets. While Hammoudeh and McAleer's (2015) review only covers the papers published in one journal, similar important contributions have also appeared in other journals, including Karnizova and Li (2014), Antonakakis et al. (2013), Jones and Olson (2013), Colombo (2013), Klößner and Sekkel (2014), and Li et al. (2015). Again, these studies have also overlooked the Chinese stock market as an affectee of US EPU shocks.

Why is a study on this neglected issue interesting? Our second consideration pertains to the relevance of the research question posed above to investors trading in the Chinese, US and even other Asian stock markets (see, e.g., Shu et al., 2015). Nowadays a Google-Scholar search for articles on China's stock markets will return about 147,000 results, and many of them conduct analyses from the perspective of international investors. Indeed, since the Chinese government launched the QFII (Qualified Foreign Institutional Investors) scheme in 2003, the Chinese A-share market has become increasingly integrated with the international market.[1] By the end of 2014, more than 280 companies from 20 countries registered as QFIIs in China, the total QFIIs' investment capital exceeded 400 billion US dollars, and there were more than 49 US companies with 60 billion US dollars or more of investment capital. Furthermore, by the end of February 2014, the total quotas issued under the QFII programme rose to $52.3 billion from $51.4 billion at the end of December 2013, and to 180.4 billion yuan ($29.44 billion) from 167.8 billion yuan under the RQFII programme, according to data released by China's State Administrate of Foreign Exchange.

Accordingly, changes in US EPU are likely to influence the behaviour of all those foreign institutional investors who partake in both the American stock market and the Chinese A- and B-share markets. This will likely enable US EPU shocks to drive the co-movements of the stock markets of the two nations. In addition, there is evidence that many Chinese retail investors tend to follow the investment trends of institutional investors including QFIIs (Hurle,

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[1] Once licensed, QFII investors are permitted to buy RMB-denominated “A shares" in China's mainland Shanghai and Shenzhen stock exchanges.

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2011). Observing changes in the trading behaviour of QFIIs brought about by US EPU shocks, Chinese retail investors may well come up with new trading decisions accordingly. As far as the US market is concerned, it is well known that institutional investors are dominant market players who will generally respond to US EPU shocks in a similar, *rational* way. These further imply the possible effect of US EPU shocks on the co-movements of the Chinese and US stock markets, despite the different compositions regarding retail and institutional investors in the stock market across China and the US.[2]

Thirdly, asset market correlations play a crucial role in constructing a well-diversified international portfolio that strikes a balance between risk and return. Li (2011) argues that the value of diversification will be overstated (understated) if investors do not take into account the increase (decrease) in downside correlation. As two examples, Vanguard's Emerging Markets Stock Index Fund once had 29% of its portfolio, and the Oppenheimer Developing Markets Fund about 20% of its portfolio, in China. The weights attached to the portfolios' exposure to China are not constant, but vary depending on, *ceteris paribus*, time-varying correlations among constituent markets. The same can also be said to the portfolios of QFIIs consisting of Chinese and US shares. Thus, their portfolio managers cannot turn a blind eye to how US policy uncertainty shocks alter the correlations, for the sake of diversification.

Many recent studies on policy uncertainty (See, e.g., the articles cited above) employ the EPU indexes developed by Baker et al. (2016), and so does the present paper. Following Li et al. (2015), we treat innovations in the EPU index as policy-induced shocks. While Li et al. (2015) consider stock-bond correlations within the US, our interest is in stock-stock correlations between China and the US.

Then, what might be the sign of the impact of US EPU shocks on the correlations? Let us carry out some reasoning. Suppose a representative risk-averse QFII holds a portfolio comprising Chinese and US shares or stock indexes. Given everything else, when the American EPU index rises (a positive EPU shock), there will be three possibilities: the investor tends to (a) sell in the US stock market and buy in the Chinese stock market; (b) sell in the US stock market while doing nothing in the Chinese stock market; and (c) sell in both markets. When the American EPU index falls (a negative EPU shock), there will also be three possibilities: the investor may raise demand for (d) both US and Chinese shares; (e) the former while not changing demand for the latter; and (f) the former while reducing the holdings of the latter. In addition, we suppose that many, if not all, other QFIIs do the same, and many, if not all, Chinese retail and institutional investors follow the suit of this representative QFII.

Then, different outcomes are possible. Following positive EPU shocks, (a) and (b) would lead to a decline, while (c) would lead to a rise, in the China-US correlations. In other words, the effect of positive EPU shocks is negative in (a) and (b) but positive in (c). Following negative EPU shocks, (d) would lead to a rise, while (e) and (f) would lead to a fall, in the China-US correlations. Put differently, the effect of negative EPU shocks is negative in (d) but positive in (e) and (f). Note that, even if no QFIIs respond to US EPU innovations, American domestic investors will: They will sell (buy) in the US stock market following a rise (fall) in policy uncertainty, also driving the China-US stock market correlations to change. Since there is, *a priori*, no knowledge or theory for us to determine which outcome should be expected, we adopt Li et al. (2015) general framework to accommodate all these possibilities and let the data speak. Specifically, this asymmetric DCC framework incorporates positive and negative EPU shocks as separate exogenous variables and then estimates their respective coefficients. Throughout this paper, we refer to the framework as ADCCX.

Employing the ADCCX framework, we examine the impacts of US EPU changes on four China-US stock market correlations. That is, we consider four well-known stock markets on the part of China: the Shanghai A-share (SHA), Shenzhen A-share (SZA), Shanghai B-share (SHB) and Shenzhen B-share (SZB) markets. The differences between A- and B-shares[3] make it necessary for us to check if the impact of US policy uncertainty innovations on the correlation would be different across them. To anticipate, our main result shows that it is absolute changes in the US EPU index that have a negative effect on each of the four correlations.[4]

Our study makes contributions to the broad literature on how economic/political uncertainty affects financial markets in general (See, for example, Boutchkova et al., 2012; Pastor and Veronesi, 2012 and 2013; and Smales, 2016), and three strands of the literature in particular, as follows.

One strand looks at the power of print in terms of the effects of news-based policy uncertainty shocks on asset markets. Whereas it has been found that policy uncertainty shocks significantly change stock market volatility and returns (See, e.g., Hammoudeh and McAleer, 2015), and stock-bond market correlations (See, e.g., Li et al., 2015) within the national context, we offer evidence that this is the case for stock-stock market co-movements and from an international perspective.

The other strand is relevant to those who are interested in the interdependence between the Chinese and other national stock markets, and embraces a large number of articles (See, e.g., Huang et al., 2000; Johnson and Soenen, 2002; Aloui et al., 2011; and Wang et al., 2011). Whereas these studies have deepened our understanding of the interdependence, one important issue omitted is how policy-related uncertainty shocks, especially the US ones, may influence such interdependence. Addressing the issue is our contribution to this strand.

The third strand deals with the power of print associated with Chinese EPU and its influences on the domestic or the Greater China economy in particular. However, to the best of our knowledge, there are limited studies in this strand (for example, Wang et al., 2014; and Kang and Ratti, 2015). Wang et al. (2014) show that higher EPU dampens corporate investment in China, while Sin (2015) suggests that changes in mainland China's EPU do not have significant influence on Taiwan but on Hong Kong. We turn to the financial market, instead of the real sector, in China, and to US EPU rather than Chinese EPU. Our results suggest that, not just Chinese own EPU shocks studied previously, but also US EPU shocks, may be relevant to fluctuations in the Chinese

[2] One might point out a research direction to differentiate between institutional and retail investors in the Chinese stock market and examine the differences in the effects of US EPU on the correlations of their respective stock movements with the US market. However, the fact that stocks are traded by both groups of investors prevents the idea from being implemented, due to the impossibility in getting the data that solely describe the trading behavior of either group.

[3] Apart from different currency denomination, for a long time, the main difference from a regulatory standpoint was that the A-share market was closed to foreign investors while the B-share market was open only to foreigners. However in 2001, the Chinese authorities tried to boost the B-share market by opening it to individual Chinese investors. And in 2003, a QFII scheme was introduced whereby selected foreign institutions were allowed to buy A-shares.

[4] Studying the aggregate Chinese stock market to see the effect of US EPU on its correlation with the US stock market is undesirable for two reasons. First, whether the results turn out to be different than or similar to the results from investigating the four Chinese sub stock markets, they would not be informative in that differences between the four sub stock markets would be obliterated away by aggregation. As a result, conclusions would unlikely be convincing and reliable (to serve, e.g., robustness check purposes). More specifically, A-share markets (SHA and SZA) can only trade A-shares, B-share markets (SHB and SZB) can only trade B-shares, and different regulations applied to different A-share markets (SHA and SZA) and to different B-share markets (SHB and SZB). For instance, traded in the SHA market are larger market-cap companies, than in the SZA market, and traded in A-share markets are larger companies than in B-share markets. So, traders with different interests/opinions about large/small shares would behave differently. All these further justify that we must study four Chinese stock markets separately, and must not group them as one market since this would make the results much less informative. Second, there are no stock price indexes available that fully cover and so represent the entire Chinese stock market. For example, even the MSCI China index does not include the mainland-traded Chinese A-shares.

economy, as the stock market is an important economic indicator (Mankiw, 2013, pp. 505–507).

The rest of the paper is organised as follows: Section 2 describes data and methodology. Section 3 presents and discusses empirical results. Section 4 concludes.

2. Data and methodology

2.1. Data

The Chinese stock market comprises four sub-markets on which the stock index data are available, and there is no single stock index that covers the entire Chinese stock market. Accordingly, we source data, from Datastream, on the Shanghai SE and the Shenzhen SE A-Share price indexes (yuan-denominated), and the Shanghai SE and the Shenzhen SE B-share price indexes (US dollar-denominated), as proxies for the four sub-markets in China. We also obtain data from Datastream on the SP500 index (US dollar-denominated) to proxy the US stock market. Since the return rates of S & P500 will be different if it is converted into the yuan, we need to check whether our results will be sensitive to this conversion. To this end, we obtain data from Datastream on the yuan-dollar exchange rate, but present the results in Appendix A (The results there remain qualitatively similar to the results reported here).

This study employs weekly data for empirical investigation.[5] The daily US EPU index is obtained from the Economic Policy Uncertainty website,[6] before being converted into weekly frequency to be consistent with the stock index data. According to the website, the US Economic Policy Uncertainty Index is daily news-based, i.e., based on newspaper archives from Access World News NewsBank service. The NewsBank Access World News database contains the archives of thousands of newspapers and other news sources from across the globe. While NewsBank has a wide range of news sources, from newspapers to magazines to newswire services, Baker et al. (2016) conduct their analysis only utilizing newspaper sources. A higher/lower value of EPU indicates that US economic policy is more/less uncertain. Many empirical studies using Baker et al.'s EPU measures have found that the measures are a good proxy for real-world economic policy uncertainty (see, e.g., Wang et al., 2014). Fig. 1 presents the time-series plot of the daily US EPU index from which we obtain its weekly counterpart (see also Fig. 7 for its percentage changes).

Weekly stock market returns are calculated as log differences of their corresponding price indexes between two successive Mondays (Wednesday-to-Wednesday returns were also tried but the results remain qualitatively similar), and so is the change rate of the weekly EPU index. Our sample period spans from January 4, 1993 to December 31, 2014, giving us 1,160 observations for each time series.[7]

Figs. 2–6 plot the weekly return rates of the five stock markets under investigation, and Fig. 7 shows the percentage change of the US EPU index. It is well known that emerging equity markets are more volatile than developed ones, and the five figures provide Chinese evidence for this phenomenon. There are more and larger spikes in

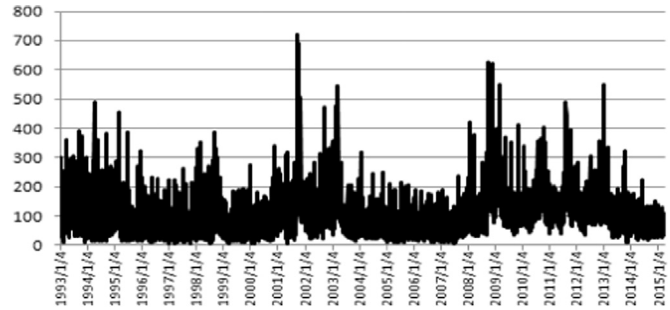

Fig. 1. The Daily US EPU Index.

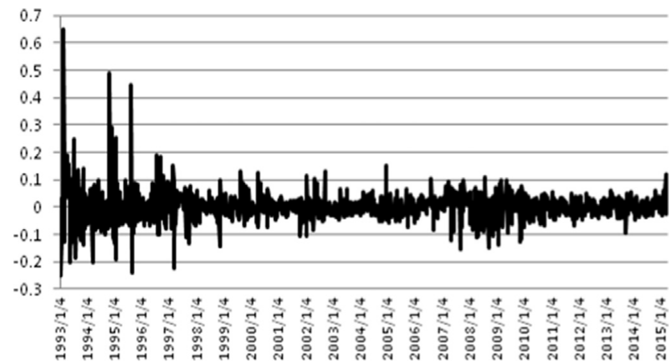

Fig. 2. Weekly return rate of the Shanghai A-share index (in ¥).

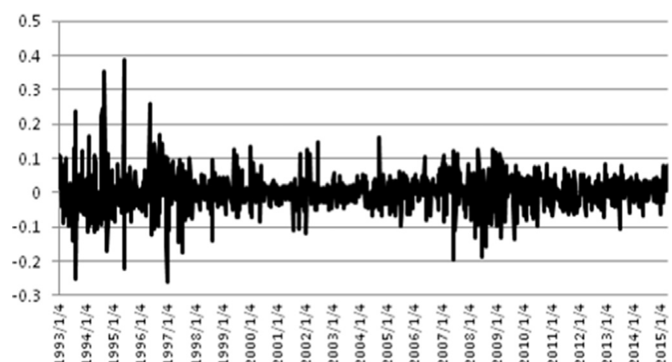

Fig. 3. Weekly return rate of the Shanghai A-share index (in ¥).

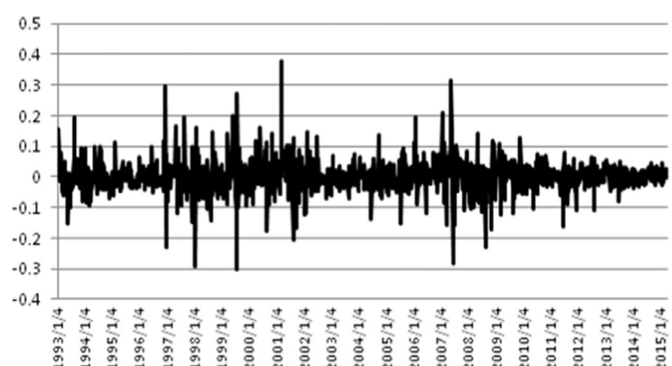

Fig. 4. Weekly return rate of the Shanghai A-share index (in $).

China's two A-share and two B-share index returns than in the S & P500 index returns. The summary statistics in Table 1 confirm the impression given by the figures. For instance, the standard deviation (S.D.) of Chinese stock market returns are all between 5 and 6, while that of the US stock market returns is only 2.496. Turning to possible time-varying volatility in returns, their ARCH statistics are all significant at a higher than 1% level. This suggests the necessity to filter

[5] In fact, we have also employed daily and monthly data. The results show that the evidence of the negative effect of the absolute changes in US EPU on China-US stock market comovements is the strongest for weekly data, less so for monthly data, and virtually nil for daily data. The possible reason may be that aggregate investors' respond to EPU changes with a lag longer than a day, but shorter than a month. Several studies involving financial time series have shown that the results with one data frequency need not hold with other data frequencies (See, for example, Chen, 2013; and Khovansky and Zhylyevskyy, 2013). The results are available upon requests.

[6] http://www.policyuncertainty.com. This website also provides data on the Chinese EPU index, but only of monthly frequency. The much smaller sample size and monthly frequency would make it uninformative to investigate the impact of the Chinese EPU shocks on the China-US stock market correlations.

[7] This is the sample period over which data on *all* the SHA, SHB, SZA and SZB stock market indexes are available for our econometric analysis that began in February 2015.

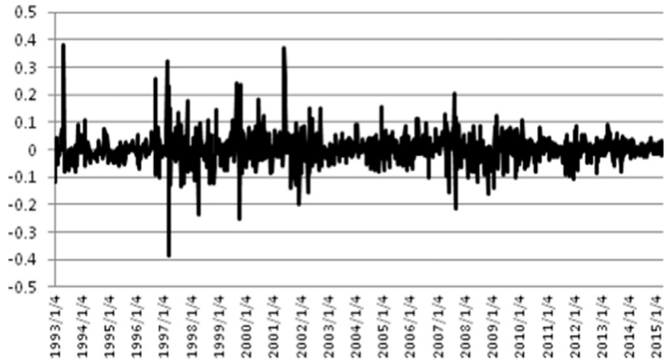

Fig. 5. Weekly return rate of the Shenzhen B-share index (in $).

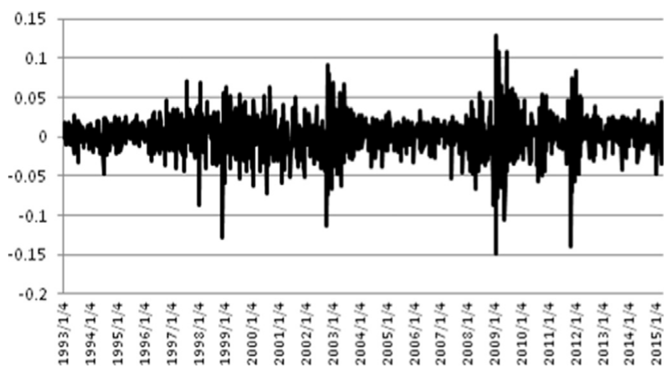

Fig. 6. Weekly return rate of the S & P 500 index (in $).

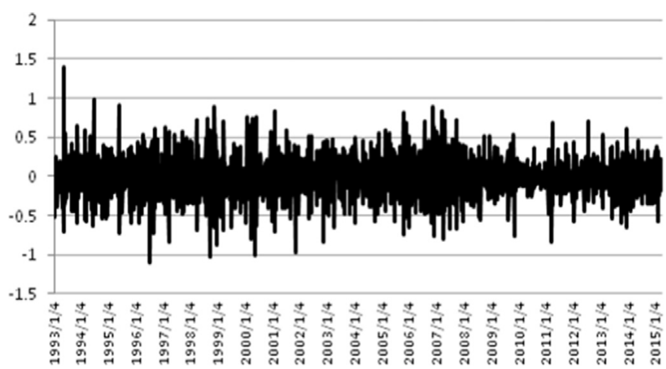

Fig. 7. Percentage change of the weekly US EPU index.

conditional volatility in the return series. Not surprisingly, the significant Jarque-Bera (J-B) test statistics indicate that the five return series do not follow the Guassian process. This prompts us to employ the quasi-maximum likelihood estimator as the DCC estimator (Engle and Sheppard, 2001)while assuming nomality for return distributions.[8]

2.2. Methodology

Let r_{it} be the return rate of market i for week t, which is assumed to follow an ARMA(1,1) process:

$$r_{it} = c_i + \phi_i r_{it-1} + z_{it} + \kappa_i z_{it-1}, \quad (i = 1, 2) \quad (Z_t|\Omega_{t-1}) \sim N[0, H_t] \tag{1}$$

where $Z_t = [z_{1t}, z_{2t}]'$, and Ω_{t-1} is the information set. Following Engle (2002), we model the covariance matrix H_t as:

$$H_t = D_t R_t D_t \tag{2}$$

[8] Engle and Sheppard (2001) point out that "When the returns have non-Guassian innovations, the DCC estimator can be interpreted as a quasi-maximum likelihood estimator".

where $D_t = diag(H_t) = diag(\sqrt{h_{1t}}, \sqrt{h_{2t}})$ is the diagonal matrix of conditional standard deviations, and $R_t = (diag(Q_t))^{-1}Q_t(diag(Q_t))^{-1}$ the conditional correlation matrix of ε_{1t} and ε_{2t}, with $\varepsilon_{it} = z_{it}/\sqrt{h_{it}}$ $(i = 1, 2)$ being two standardized residuals.

In modelling conditional variances h_{1t} and h_{2t}, we allow for possible leverage effects by estimating GJR-GARCH(1,1):

$$h_{it} = \omega_i + \delta_i z_{it-1}^2 + \zeta_i (z_{it-1}^-)^2 + \theta_i h_{it-1}, \quad (i = 1, 2) \tag{3}$$

where $z_{it}^- = I(z_{it} \geq 0)^\circ z_{it}$ ("°" denotes the Hadamard product). Eq. (3) nests a standard GARCH(1,1) model where ξ_i is zero (i.e., where no leverage effects are present). Using a GJR-GARCH model is to prevent the leverage effects, if any, from biasing the subsequent estimation of correlations.

The time-varying correlation coefficient between ε_{1t} and ε_{2t}, $\rho_{12t} = q_{12t}/\sqrt{q_{11t}q_{22t}}$, is the element in R_t, and q_{12t}, q_{11t} and q_{22t} are the elements in Q_t. Thus, to obtain the estimates of ρ_{12t}, one must estimate Q_t. Li (2011) and Li et al. (2015) demonstrate that the following asymmetric DCC model with exogenous variables (hence labelled as ADCCX throughout this paper) works very well,

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B) + A'e_{t-1}e_{t-1}'A + B'Q_{t-1}B + \eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^- \tag{4}$$

where one attempts to take into account the asymmetric effects of non-EPU and EPU shocks on correlations. As such, we employ this model. In Eq. (4), the unconditional correlation matrix $\overline{Q} = \begin{pmatrix} 1 & \overline{\rho}_{12} \\ \overline{\rho}_{12} & 1 \end{pmatrix}$, $A = \begin{pmatrix} \alpha_1 & 0 \\ 0 & \alpha_2 \end{pmatrix}$, $B = \begin{pmatrix} \beta_1 & 0 \\ 0 & \beta_2 \end{pmatrix}$, $e_t = (\varepsilon_{1t} + \gamma_1, \varepsilon_{2t} + \gamma_2)'$ (γ_1 and γ_2 capture the asymmetric effects of non-EPU shocks ε_{1t} and ε_{2t}), $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$, $\Delta\xi_t = 100\times(\ln\xi_t - \ln\xi_{t-1})$ (ξ denotes the US EPU index), $\Delta\xi_t^+ = I(\Delta\xi_t \geq 0)^\circ\Delta\xi_t$, and $\Delta\xi_t^- = I(\Delta\xi_t < 0)^\circ\Delta\xi_t$. Eq. (4) embraces the standard DCC model of Engle and Sheppard (2001) augmented with $\Delta\xi_t$, where $\gamma_1 = \gamma_2 = 0$. For convenience, we present the element version of (4) below:

$$q_{11t} = (1 - \alpha_1^2 - \beta_1^2) + \alpha_1^2(\varepsilon_{1t-1} + \gamma_1)^2 + \beta_1^2 q_{11t-1} + \eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^-$$

$$q_{12t} = \overline{\rho}_{12}(1 - \alpha_1\alpha_2 - \beta_1\beta_2) + \alpha_1\alpha_2(\varepsilon_{1t-1} + \gamma_1)(\varepsilon_{2t-1} + \gamma_2) + \beta_1\beta_2 q_{12t-1} + \eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^-$$

$$q_{22t} = (1 - \alpha_2^2 - \beta_2^2) + \alpha_2^2(\varepsilon_{2t-1} + \gamma_2)^2 + \beta_2^2 q_{22t-1} + \eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^-$$

The parameter restrictions are $1 - \alpha_1^2 - \beta_1^2 > 0$, $1 - \alpha_1\alpha_2 - \beta_1\beta_2 > 0$ and $1 - \alpha_2^2 - \beta_2^2 > 0$.

Relevant to the focus of this study, the term $\eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^-$ deserves some remarks. There are three possibilities. (i) $\eta^+ = \eta^- = \eta$. Then, $\eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^- = \eta(\Delta\xi_{t-1}^+ + \Delta\xi_{t-1}^-) = \eta\Delta\xi_{t-1}$, and a rise and a fall in the EUP index would have opposite but symmetric effects on the subsequent China-US stock market correlations. (ii), $\eta^+ = -\eta^- = \eta$. In this case, $\eta^+\Delta\xi_{t-1}^+ + \eta^-\Delta\xi_{t-1}^- = \eta(\Delta\xi_{t-1}^+ - \Delta\xi_{t-1}^-) = \eta|\Delta\xi_{t-1}|$, and a rise and a fall in the EUP index would change the future China-US market correlations in the same direction. (iii), $\eta^+ \neq -\eta^-$ (or $\eta^+ \neq \eta^-$), which is the general case. We perform tests for the four China-US stock market correlations, to ascertain which case is true in each of them.

It should be of interest to investigate whether the effects of US EPU shocks on the China-US stock market co-movements have changed their signs over the sample period. To this end, we consider a structural break in Eq. (4). There might have been a very large number of possible events, including the 2007–2009 global financial crisis, that have had structural- change effects on the co-movements. However, it is beyond the scope of this study and would make our undertakings intractable to try all of them. Accordingly, we focus on one event most relevant to the question posed above: the advent of the QFII scheme in May 2003. The caveat, however, is that we do so not to test whether or not the event gave rise to a break, but rather to make sure that the break, if present, has not altered the direction in which the US EPU shocks affect the co-movements.

Table 1
Summary statistics.

Series	Mean (%)	Min (%)	Max (%)	S.D.	Skewness	Kurtosis	ARCH	J-B
SHA's return	0.0013	-0.2499	0.6518	5.603	2.2905	25.706	9.342***	32663***
SZA's return	0.1738	-25.823	38.637	5.279	0.5260	6.6744	80.94***	2183***
SHB's return	0.1337	-30.115	37.724	5.496	0.3126	6.9903	44.59***	2455***
SZB's return	0.0017	-0.3880	0.3806	5.414	0.7561	10.008	87.86***	4904***
S & P500's return	0.0015	-0.1491	0.1295	2.496	-0.4147	4.6429	148.9***	1060***
ΔlnEPU	-0.0765	-1.1072	1.3979	30.37	-0.0365	0.6843	80.24***	22.87***

Note. The sample size is 1,160, from January 4, 1993 to March 23, 2015. S.D. denotes standard deviation. J-B denotes the Jarque-Bera statistic.
*** Significance at the 1% level.

We estimate the parameters in the GJR-GARCH and ADCCX models by applying the two-stage procedure proposed by Engle and Sheppard (2001). As noted above, this procedure uses the quasi-maximum-likelihood estimator (QMLE), as the distributions of standardized residuals ε_{1t} and ε_{2t} do not satisfy the normality assumption. The two authors establish the consistency and asymptotical normality of the QMLE, although it is not efficient. To mitigate the inefficiency problem, we modify the standard errors of coefficient estimates according to the theorems provided in Engle and Sheppard (2001) for the two-stage procedure.

3. Empirical results

3.1. Preliminary results

Table 2 presents the estimation results of the GJR-GARCH model for the five return series. Only the S & P500 return series is plagued by the leverage effect, with ζ in Eq. (3) being significantly greater than zero. China's two A-share and two B-share return series do not have such an effect in their volatilities. In fact, even when $(z_{it-1}^{-})^2$ is replaced by $(z_{it-1}^{+})^2$, the parameter ζ is still estimated to be zero. Thus, as far as China's four markets are concerned, the GJR-GARCH model collapses to the standard GARCH model. In addition, the insignificant Ljung-Box statistics of ε_{it} and ε_{it}^2 suggest the employed ARMA(1,1) and GJR-GARCH(1,1) models do a good job in ensuring the standardized residuals ε_{it} are i.i.d.

Table 3 summarises the estimation results of the ADCCX model, ignoring structural change, for the four China-US stock market correlations. The most important observation to make is that, in each Panel, the coefficients η^+ and η^- are estimated to be statistically significant at a higher than 1% level: η^+= -0.0817 and η^-= 0.0636 in Panel A; η^+= -0.0276 and η^- = 0.0063 in Panel B; η^+= -0.0639 and η^-= 0.1000 in Panel C; and η^+= -0.0656 and η^-= 0.1490 in Panel D. To confirm these results, we test the hypothesis that η^+ and η^- are jointly zero. The likelihood ratio test (LRT) statistics allow us to decisively reject the hypothesis at a higher than 1% level for three, and at a higher than 5% level for one China-US stock-stock correlation: *LRT*=23.38 in Panel A; *LRT*=7.580 in Panel B; *LRT*=23.30 in Panel C; and *LRT*=50.74 in Panel D. Whether η^+=-η^- or η^+=η^- will be investigated in Subsection 3.2 where the results of the new model allowing for structural change are reported.

Another, albeit less important, finding pertains to the γ parameter. The inclusion of this parameter in the ADCCX model has the advantage of capturing the asymmetric effects of non-EPU shocks (Li, 2011 and Li et al., 2015). In view of this, we employ the model to control for the effects, thereby ensuring that the effects of EPU shocks, if present, are not due to those of their non-EPU counterparts. Table 3 illustrates that most of the γ coefficient estimates are both statistically and economically significant, though one of them is only economically significant (see γ_1=0.1447 in Panel C). Despite of these, however, the significances of the η^+ and η^- parameters are still consistently high. Thus, non-EPU shocks (e_{it}) do not contain information about EPU shocks ($\Delta\xi_t$), which suggests that incorporating the latter in the ADCC model is an effective way to reveal their own effects.

Table 2
Estimation of the GJR-GARCH model.

Market return	ω_1	δ_1	ζ_1	θ_1	$Q_\varepsilon(18)$	$Q_{\varepsilon^2}(18)$
SHA's return	0.1688	0.0816	0	0.9180***	14.90	14.44
SZA's return	0.1690	0.0572	0	0.9392***	13.33	21.76
SHB's return	0.2272	0.0703***	0	0.9257***	16.77	16.62
SZB's return	0.3328	0.0780**	0	0.9200***	19.33	6.825
S & P500's return	0.2279***	0.0081	0.2483***	0.8270***	11.04	7.108

Note. $Q_\varepsilon(18)$ denotes the Q statistic for ε with a lag length of 18. $Q_{\varepsilon^2}(18)$ denotes the Q statistic for ε^2 with a lag length of 18.
*** Significance at the 1% level.
** Significance at the 5% level.

3.2. Robustness check via allowing for structural change

Did the correlation impacts of US EPU shocks change their directions during the sample period under investigation? The question is relevant given that the Chinese stock markets have undergone some important reforms such as the implementation of the QFII scheme. As mentioned above, the present study is only interested in whether the signs of the η^+ and η^- parameters remain unchanged over the investigated sample period as reported in Table 3. Not making the task intractable by searching all possible events, we focus on one episode - the QFII reform.

The first two QFII investors admitted to trade China's A-shares were UBS AG and Nomura Securities Co., Ltd, approved on May 23, 2003. Less than two weeks later, on June 5 2003, two American corporations, Morgan Stanley & Co. International Limited and Citigroup Global Markets Limited, acquired the QFII status; and so on. Although the QFII reform has been a gradual process and so its effect could not be abrupt, a practically feasible way for conducting DCC econometric analysis is to look at the difference in the average effects on correlations between the pre- and the post-QFII period. Based on these considerations, we therefore pick May 26, 2003 as a break date in the sample period. One needs to be cautious, however, that the structural break, if detected, should not be taken as sure evidence to claim that its cause was the QFII event.

Table 4 sets out the results for the correlations of China's four stock markets with the US stock market. All the ADCCX parameters, including the unconditional correlation coefficient, are allowed to experience a break at the date chosen above. The subscript "*E*" denotes the pre-QFII period (from January 4, 1993 to May 19, 2003), and the subscript "*L*" represents the post-QFII period (from May 26, 2003 to the end of our sample). Again, what this study is most concerned with are the signs of the four η parameters: η_E^+, η_L^+, η_E^- and η_L^-. The last two columns of the four panels display that η_E^+ and η_L^+ are all estimated to be negative, while η_E^- and η_L^- to be positive, with fifteen estimates at a higher than 1% significance level and one at the 5% level (referring to η_L^+= -0.0094 in Panel B). This is so, despite the fact that the structural

Table 3
Estimation of ADCCX models without structural change.

Panel A SHA vs. S & P500								
α_1	β_1	γ_1	α_2	β_2	γ_2	η^+	η^-	*LLF*
0.1265***	0.9927***	0.3543***	0.3199***	0.6465***	0.7123***	-0.0817***	0.0636***	-5868.48
H_0: $\eta^+ = 0$ and $\eta^- = 0$. H_1: $\eta^+ \neq 0$ and/or $\eta^- \neq 0$. *LRT* = 23.38*** with d.f. = 2.								
Panel B SZA vs. S & P500								
α_1	β_1	γ_1	α_2	β_2	γ_2	η^+	η^-	*LLF*
0.0704***	0.9977***	0.4136***	0.3098***	0.5334***	0.7932***	-0.0276***	0.0063***	-5930.00
H_0: $\eta^+ = 0$ and $\eta^- = 0$. H_1: $\eta^+ \neq 0$ and/or $\eta^- \neq 0$. *LRT* = 7.58** with d.f. = 2.								
Panel C SHB vs. S & P500								
α_1	β_1	γ_1	α_2	β_2	γ_2	η^+	η^-	*LLF*
0.0958***	0.9962***	0.1447	0.2761***	0.3817***	0.8106***	-0.0639***	0.1000***	-5995.38
H_0: $\eta^+ = 0$ and $\eta^- = 0$. H_1: $\eta^+ \neq 0$ and/or $\eta^- \neq 0$. *LRT* = 23.30*** with d.f. = 2.								
Panel D SZB vs. S & P500								
α_1	β_1	γ_1	α_2	β_2	γ_2	η^+	η^-	*LLF*
0.1054***	0.9938***	-0.3654***	0.3462***	0.6832***	0.6663***	-0.0656***	0.1490***	-5970.14
H_0: $\eta^+ = 0$ and $\eta^- = 0$. H_1: $\eta^+ \neq 0$ and/or $\eta^- \neq 0$. *LRT* = 50.74***.								

Note. Both SHA and SZA are yuan-denominated, both SHB and SZB are US-dollar denominated, and S & P500 is US-dollar-denominated. *LLF* is the value of the log likelihood function when maximised. *LRT* denotes the log likelihood ratio test statistic. The reported estimates of η^+ and η^- are multiplied by 100.
*** Significance at the 1% level.

break in the unconditional correlation ($\bar{\rho}$), and in all other ADCCX model parameters (α's, β's and γ's), is allowed/controlled for. These results imply that the structural break in the system does not alter the correlation impacts of US EPU shocks qualitatively though quantitatively, consistent with the findings reported in Table 3.

We now explore the issue of symmetry or asymmetry with which positive and negative US policy uncertainty shocks impact each of the four correlations; and this is done for respectively the pre- and the post-break period. Specifically, we impose the restrictions $\eta_E^+ = -\eta_E^-$ (for the pre-break period) and $\eta_L^+ = -\eta_L^-$ (for the post-break period), and test this joint hypothesis. The four corresponding LRT statistics in Table 4 (*LRT* = 0.02 in Panel A; *LRT* = 2.48 in Panel B; *LRT* = 1.68 in Panel C; and *LRT* = 2.96 in Panel D) do not allow us to reject the joint null, for all the four correlation series. Meanwhile, we also test the restrictions $\eta_E^+ = \eta_E^-$ (for the pre-break period) and $\eta_L^+ = \eta_L^-$ (for the post-break period). The four corresponding LRT statistics in Table 4 (*LRT* = 9.35 in Panel A; *LRT* = 10.14 in Panel B; *LRT* =29.34 in Panel C; and *LRT* =52.90 in Panel D) enable us to decisively reject the joint null, since they are all statistically significant at a higher than 1% level.

The aforementioned test results from Table 4 suggest that the last two terms in Eq. (4) can be expressed as $\eta_E^+\Delta\xi_{t-1}^+ + \eta_E^-\Delta\xi_{t-1}^- = \eta_E^+\Delta\xi_{t-1}^+ - \eta_E^+\Delta\xi_{t-1}^- = \eta_E|\Delta\xi_{t-1}|$ over the pre-break period, and as $\eta_L^+\Delta\xi_{t-1}^+ + \eta_L^-\Delta\xi_{t-1}^- = \eta_L^+\Delta\xi_{t-1}^+ - \eta_L^+\Delta\xi_{t-1}^- = \eta_L|\Delta\xi_{t-1}|$ over the post-break period, for each correlation. If η_E and η_L all take a negative value, then a positive EPU innovation $\Delta\xi_{t-1}^+$ and a negative EPU innovation $\Delta\xi_{t-1}^-$ would both tend to lower the subsequent correlations. Thus, we go further to re-estimate Eq. (4) but with the restrictions $\eta_E^+ = -\eta_E^-$ (= η_E) and $\eta_L^+ = -\eta_L^-$ (= η_L) imposed. Table 5 reports the re-estimation results. One can see that the estimates of η_E and η_L are indeed negative and statistically significant at the 1% level for the four correlation series. Based on the logic behind the results in Tables 4 and 5, it is reasonable to use the ADCCX models in Table 5 to make economic sense of their results. In what follows, we elaborate a bit more on the rationale of this logic while making economic sense of the results.

Earlier in the introduction section, we put forward several possible outcomes of our work, as well as their rationales. Recall one of them here. Following a rise in US policy uncertainty ($\Delta\xi_{t-1} > 0$, i.e., $\Delta\xi_{t-1}^+$) hence a deterioration of American economic environment, there would tend to be more sales in the US stock market. Given everything else, this generally may lead to subsequent declines in the China-US stock market correlations (i.e., $\Delta\xi_{t-1}^+$has a negative effect on $\rho_{12,t}$). Conversely, when US policy becomes less uncertain ($\Delta\xi_{t-1} < 0$, i.e., $\Delta\xi_{t-1}^-$), there would be perceived improvement in American economic outlook, which encourages purchases in the US stock market. *Ceteris paribus*, this generally would again tend to result in declines in the subsequent correlations (i.e., $\Delta\xi_{t-1}^-$ has a positive effect on $\rho_{12,t}$). The results in Table 5 (and Table 4) apparently point to this outcome.

Our results can be compared with those of several similar studies on securities markets, although they have focused on stock-bond correlations. For instance, Li et al. (2015) find that innovations in the US EPU index impact negatively, albeit asymmetrically, on the subsequent stock-bond correlations within the US. An earlier study by Connolly et al. (2005) also detects negative effects of absolute changes in uncertainty (measured by implied volatility) on the future stock-bond correlation. To the best of our knowledge, there have been no studies on how stock-stock correlations respond to EPU shocks. As such, our results complement the related empirical findings in Li et al. (2015) and Connolly et al. (2005) in three main aspects: The evidence we provide is (i) on stock-stock correlations rather than stock-bond correlations, (ii) from an international perspective rather than within a country, and (iii) with the effect of a negative EPU shock being positive, rather than being negative as in Li et al. (2015).

3.3. Simulation analysis

Some results from Table 5 were not yet mentioned and discussed in the previous subsection. These results are economically interesting, and so deserve a section for discussion.

It seems that the SHA-S & P500 and SZB-S & P500 correlations responded *more* strongly to US EPU shocks in the pre-break than in the post-break period: η_E=-0.1140 < η_L=-0.0707 for the former correlation and η_E=-0.2276 < η_L=-0.0705 for the latter. And, accompanying this, their unconditional correlations have *risen*: $\bar{\rho}_L$= 0.2205 > $\bar{\rho}_E$ = -0.0601 for the former and $\bar{\rho}_L$= 0.2522 > $\bar{\rho}_E$ = 0.0363 for the latter. Also, it appears that the SZA-S & P500 and SHB-S & P500 correlations were *less* responsive to the EPU shocks in the pre-break than in the post-break period: η_E=-0.0195 > η_L=-0.0464 for the former correlation and η_E= -0.1140 > η_L=-0.1820 for the latter. And, along with this, their unconditional correlations have *fallen*: $\bar{\rho}_L$= 0.0097 < $\bar{\rho}_E$ = 0.0613 for the former correlation and $\bar{\rho}_L$= 0.0443 > $\bar{\rho}_E$ = 0.0529 for the latter.[9] However, the responsiveness of a correlation to the change in the exogenous variable depends not just on the

[9] The negative relation between $|\bar{\rho}|$ and $|\eta|$ across two subsample periods is not new and has been documented in Li (2011) and Li et al. (2015). This may be due to the restriction $|\rho| \le 1$.

Table 4
Estimation of the ADCCX model with structural change in all parameters.

Panel A SHA vs. S & P500

α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.1382***	0.9916***	0.5150***	0.3123***	0.5600***	0.4021	-0.1050***	0.1396***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.1116***	0.9941***	0.2195	0.3666***	0.5322**	0.9797***	-0.0783***	0.0626***

LLF = -5857.16.
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT* = 0.02. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=9.35***

Panel B SZA vs. S & P500

α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.1017***	0.9948***	0.4122**	0.3120***	0.6620***	0.2795	-0.0166***	0.0205***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.5E-10	0.9931***	0.0576	0.3926***	0.0202	1.1415***	-0.0094**	0.0645***

LLF = -5925.96.
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT* = 2.48. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=10.41***

Panel C SHB vs. S & P500

α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.1042***	0.9957***	-0.2844***	0.2422***	0.7657***	0.3192	-0.1041***	0.1254***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.8E-10	0.9636***	-0.0070	0.3932***	0.2E-06	1.1331***	-0.2620***	0.1507***

LLF = -5992.21.
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT*=1.68. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=29.34***

Panel D SZB vs. S & P500

α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.1226***	0.9948***	-0.4830***	0.3297***	0.2383***	0.7071**	-0.2830***	0.1836***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.0977***	0.9956***	-0.5329***	0.3777***	0.3927***	1.1289***	-0.0558***	0.0922***

LLF = -5960.22.
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT* = 2.96. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=52.90***

Note. Both SHA and SZA are yuan-denominated, both SHB and SZB are US-dollar-denominated, and S & P500 is US-dollar-denominated. *LLF* is the value of the log likelihood function when maximised. *LRT* denotes the log likelihood ratio test statistic. The reported estimates of η^+ and η^- are multiplied by 100.
*** Significance at the 1% level.
** Significance at the 5% level.

parameter associated with the variable, but also on other parameters and variables in the ADCCX model.[10] Simulation analysis is an intuitive way to uncover the full difference in the correlation responsiveness between the pre- and the post-break period for each Chinese stock market. This subsection thus carries out simulation analysis based on the ADCCX model in Table 5.

It may be useful to begin with the time-series plots of the four correlations depicted in Figs. 8–11. A common observation is that the four correlations are time-varying and experience a structural break at the chosen date (May 26, 2003). However, while the SHA-S & P500 and the SZB-S & P500 correlation have risen significantly on average, the SZA-S & P500 and the SHB-S & P500 correlation have fallen slightly on average. The four figures provide us with the full pictures of actual, historical correlations. To see how a change in US EPU innovations $\Delta\xi_{t-1}$ impacts the subsequent correlations over the sample period, we resort to the simulation exercises described below.

Specifically, we let $\Delta\xi_{t-1}^+$ increase and $\Delta\xi_{t-1}^-$ decrease respectively, at a chosen time point t-1 only, in the pre-break and then the post-break period. The former is termed as "a positive shock to positive EPU innovations", while the latter as "a negative shock to negative EPU innovations". A positive/negative shock is of the size equal to 1.5 standard deviation of $\Delta\xi_t$. The exercises are done for each of the four correlations in question. These one-time perturbations lead to four counterfactual paths of each correlation, as delineated in Figs. 12–16. In each figure, Panels (a) and (c) concern the pre-break period, and Panels (b) and (d) pertain to the post-break period. The historical path is represented by a solid line and the counterfactual path by a dashed line. Note that choosing different time points will produce different results only quantitatively - i.e., this will not alter the conclusions qualitatively.

Fig. 12 is associated with the SHA-S & P500 correlation. Panels (a) and (b) reveal that a transitory positive shock to positive EPU innovations would subsequently cause the correlation to decline more from its historical path in the pre-break than in the post-break period (The two respective initial declines are: -0.0623 < -0.0249). The same can also be said to Panels (c) and (d) where a transitory negative shock to negative EPU innovations is considered (The two respective initial declines are: -0.0649 < -0.0256). These confirm the prediction of the econometric results (η_E = -0.1140 < η_L = -0.0707) in Panel A of Table 5.

Fig. 13 pertains to the SZA-S & P500 correlation. As revealed by Panels (a) and (b), a transitory positive shock to positive EPU innovations would subsequently move the correlation down from its historical path more in the post-break than in the pre-break period (The two respective initial declines are: -0.0225 < -0.0084). The same applies to panels (c) and (d) where a transitory negative shock to negative EPU innovations is considered (The two respective initial declines are: -0.0204 < -0.0089). These confirm the prediction of the econometric results (η_E = -0.0195 > η_L = -0.0464) in Panel B of Table 5.

Fig. 14 is in regard to the SHB-S & P500 correlation. Panels (a) and (b) show that a transitory positive shock to positive EPU innovations

[10] It can be shown that $\partial\rho_{12t}/\partial|\Delta\xi_{t-1}| = \eta(1 - q_{12t}/2)/\sqrt{q_{11t}q_{22t}}$: η alone cannot completely determine the value of $\partial\rho_{12t}/\partial|\Delta\xi_{t-1}|$ which measures the correlation impact of the EPU shocks.

Table 5
Re-estimation of the ADCCX model in Table 4 with restrictions $\eta_E^+ = -\eta_E^-$ (= η_E) and $\eta_L^+ = -\eta_L^-$ (= η_L) imposed.

Panel A SHA vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1382***	0.9914***	0.5069***	0.3126***	0.5501**	0.4084	-0.1140***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.1121***	0.9942***	0.2221	0.3667***	0.5212**	0.9875***	-0.0707***
LLF =-5857.17. $\bar{\rho}$ = 0.0833. $\bar{\rho}_E$ = -0.0601. $\bar{\rho}_L$ = 0.2205.						
Panel B SZA vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1038***	0.9948***	0.4099**	0 .3104***	0 .6682***	0.2723	-0.0195***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.6E-09	0 .9885***	0.0691	0.3886***	0.5971***	0.9455***	-0.0464***
LLF = -5927.20. $\bar{\rho}$ = 0.0349. $\bar{\rho}_E$ = 0.0613. $\bar{\rho}_L$ = 0.0097.						
Panel C SHB vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1080***	0.9940***	-0.2658	0.2422**	0.7657***	0.3191	-0.1140***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.5E-08	0.9674***	-0.1E-06	0.4064***	0.0042	1.0616***	-0.1820***
LLF = -5993.05. $\bar{\rho}$ = 0.0485. $\bar{\rho}_E$ = 0.0529. $\bar{\rho}_L$ = 0.0443.						
Panel D SZB vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1226***	0.9947***	-0.4830***	0.3187***	0.2506***	0.7071***	-0.2276***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.0977***	0.9940***	-0.5329***	0.3553***	0.3927***	1.1289***	-0.0705***
LLF = -5961.70. $\bar{\rho}$= 0.1406. $\bar{\rho}_E$ = 0.0363. $\bar{\rho}_L$= 0.2522.						

Note. Both SHA and SZA are yuan-denominated, both SHB and SZB are US-dollar-denominated, and S & P500 is US-dollar-denominated. *LLF* is the value of the log likelihood function when maximised. *LRT* denotes the log likelihood ratio test statistic. The reported estimates of η^+ and η^- are multiplied by 100. $\bar{\rho}$, $\bar{\rho}_E$ and $\bar{\rho}_L$ are unconditional correlations over, respectively, the whole sample period, the pre-break sample period and the post-break sample period. *** Significance at the 1% level. ** Significance at the 5% level. The last two terms in Eq. (4) now become $\eta_E^+\Delta\xi_{t-1}^+ + \eta_E^-\Delta\xi_{t-1}^- = \eta_E|\Delta\xi_{t-1}|$ over the pre-break period, and $\eta_L^+\Delta\xi_{t-1}^+ + \eta_L^-\Delta\xi_{t-1}^- = \eta_L|\Delta\xi_{t-1}|$ over the post-break period.

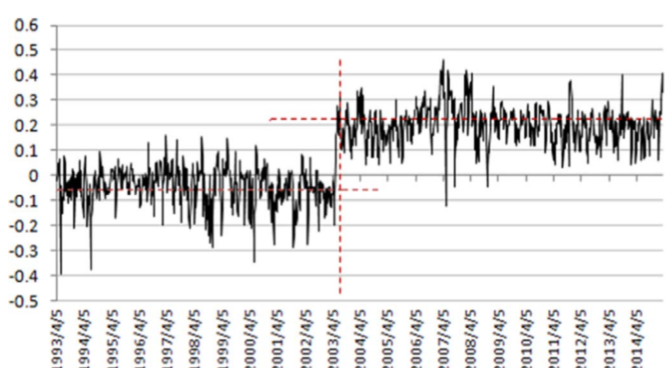

Fig.8. SHA-S & P500 correlations (conditional) SHA-S & P500 correlations (unconditional).

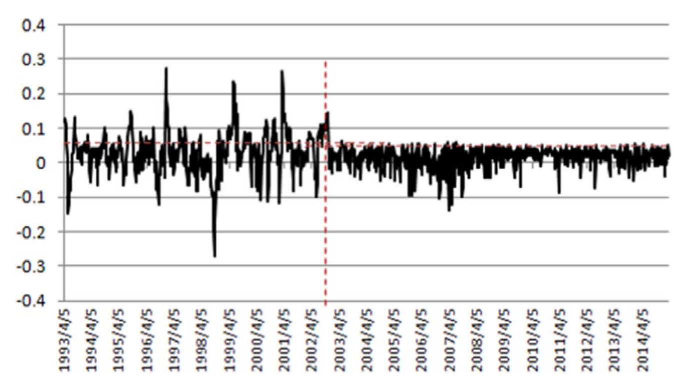

Fig. 10. SHB-S & P500 correlations (conditional) SHB-S & P500 correlations (unconditional).

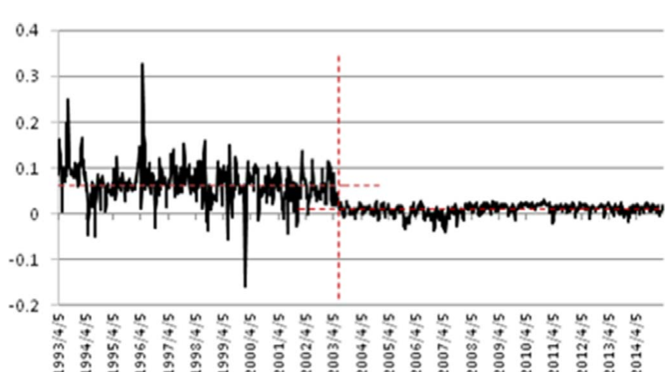

Fig. 9. SZA-S & P500 correlations (conditional) SZA-S & P500 correlations (unconditional).

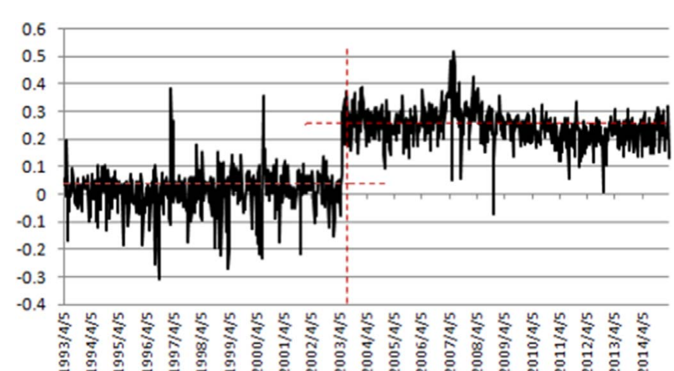

Fig.11. SZB-S & P500 correlations (conditional) SZB-S & P500 correlations (unconditional).

would give rise to a greater decline in the subsequent correlation from its historical path in the post-break than in the pre-break period (The two respective initial declines are: -0.0972 < -0.0531). The same is valid to panels (c) and (d) where a transitory negative shock to negative EPU innovations is considered (The two respective initial declines are: -0.0849 < -0.0528). These are consistent with the econometric results

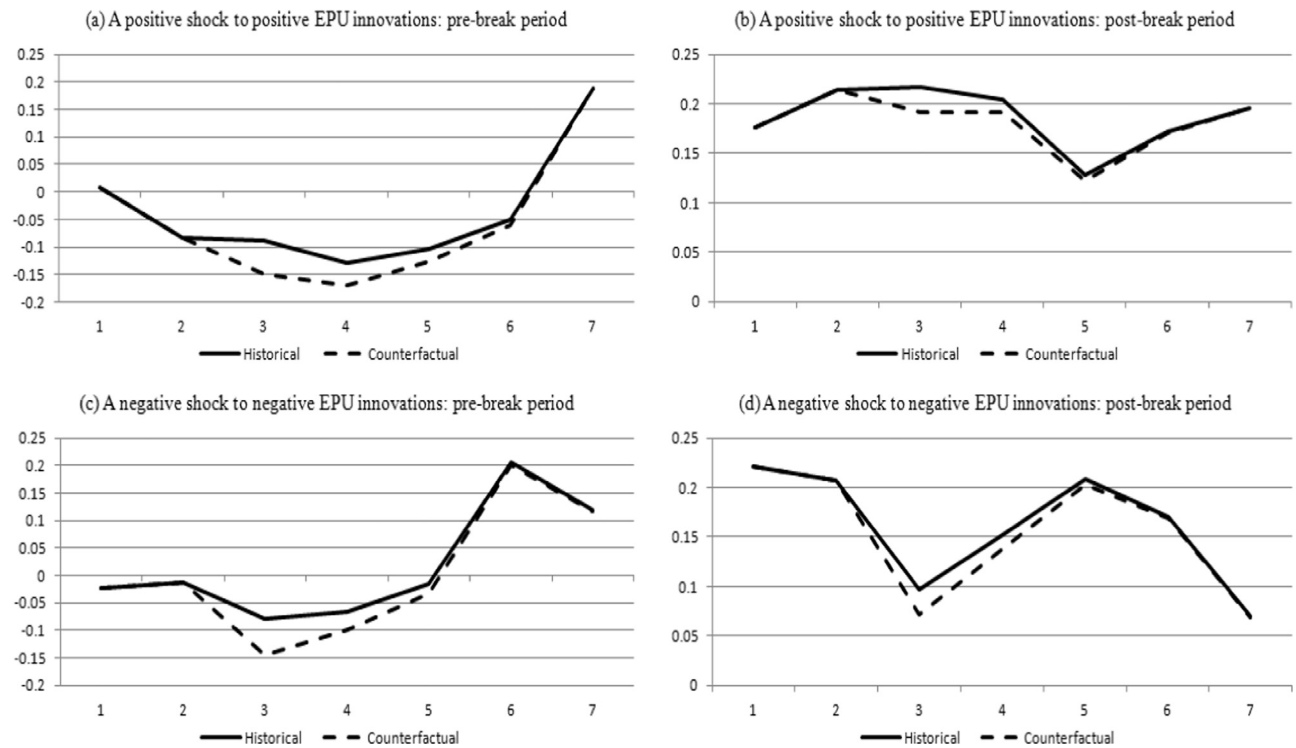

Fig. 12. Implications of transitory US EPU shocks for the SHA-S & P500 correlation.

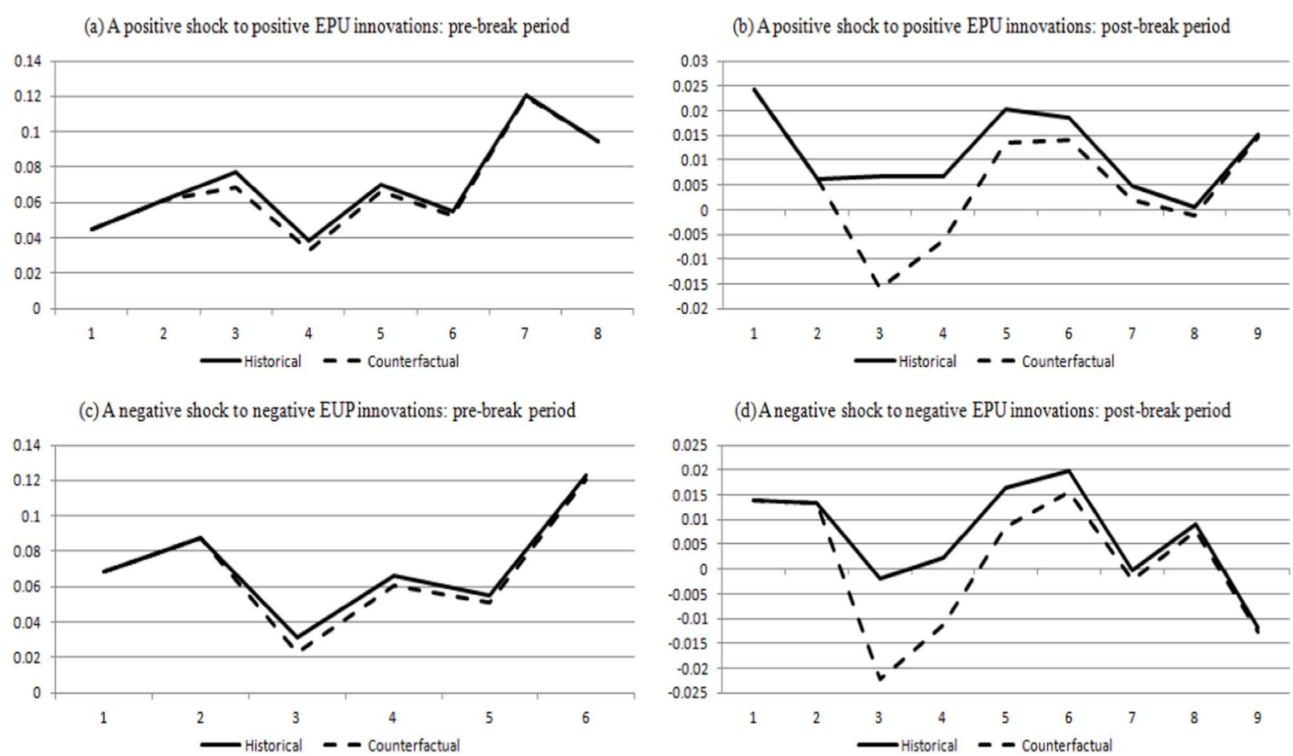

Fig. 13. Implications of transitory US EPU shocks for the SZA-S & P500 correlation.

(η_E = -0.1140 > η_L = -0.1820) in Panel C of Table 5.

Fig. 15 turns to the SZB-S & P500 correlation. One can see from Panels (a) and (b) that a transitory positive shock to positive EPU innovations would make the subsequent correlation fall more from its historical path in the pre-break than in the post-break period (The two respective initial declines are: -0.0607 < -0.0249). The same is true for panels (c) and (d) where a transitory negative shock to negative EPU innovations is considered (The two respective initial declines are: -0.0649 < -0.0256). These corroborate the econometric results (η_E = -0.2276 < η_L = -0.0705) in Panel D of Table 5.

In the above-discussed four figures, a one-time rise in the absolute value of US EPU innovations (i.e., a rise in $\Delta\xi_{t-1}^{+}$ and a fall in $\Delta\xi_{t-1}^{-}$) would have a declining effect on the correlations that lasts for a varying number of weeks depending on which Chinese share market is in

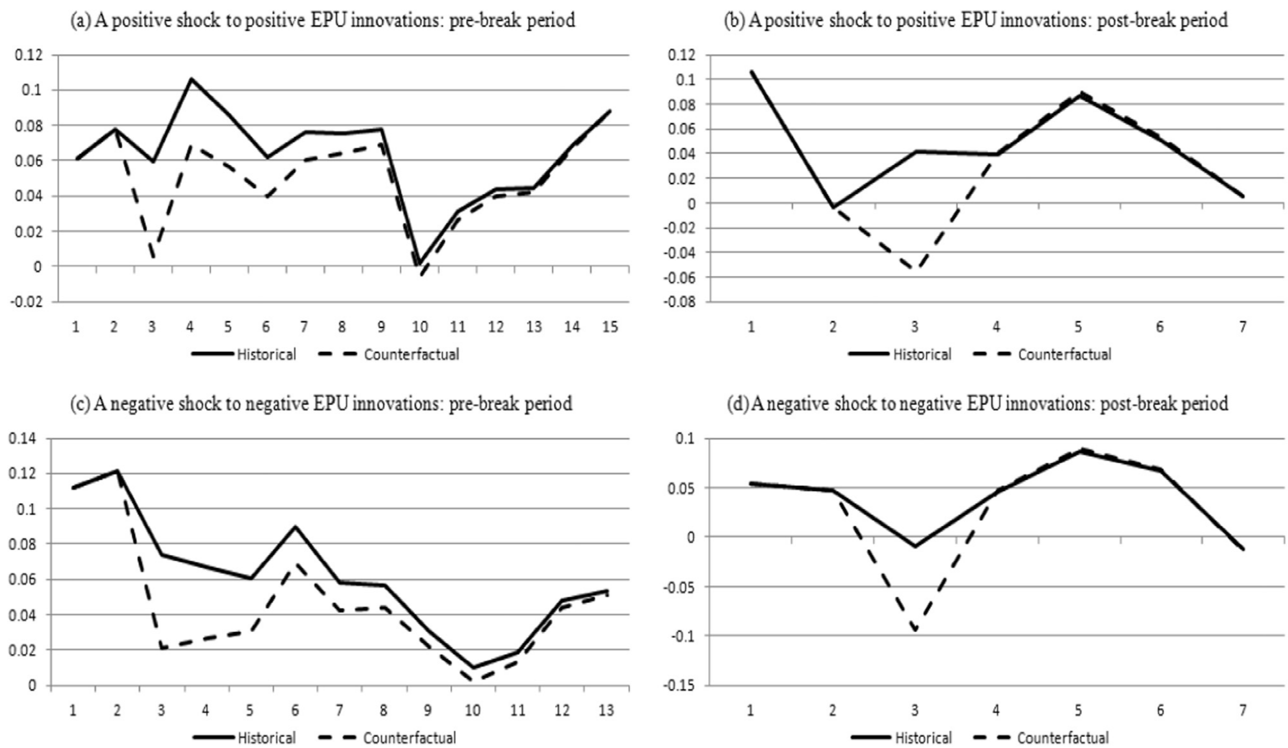

Fig. 14. Implications of transitory US EPU shocks for the SHB-S & P500 correlation.

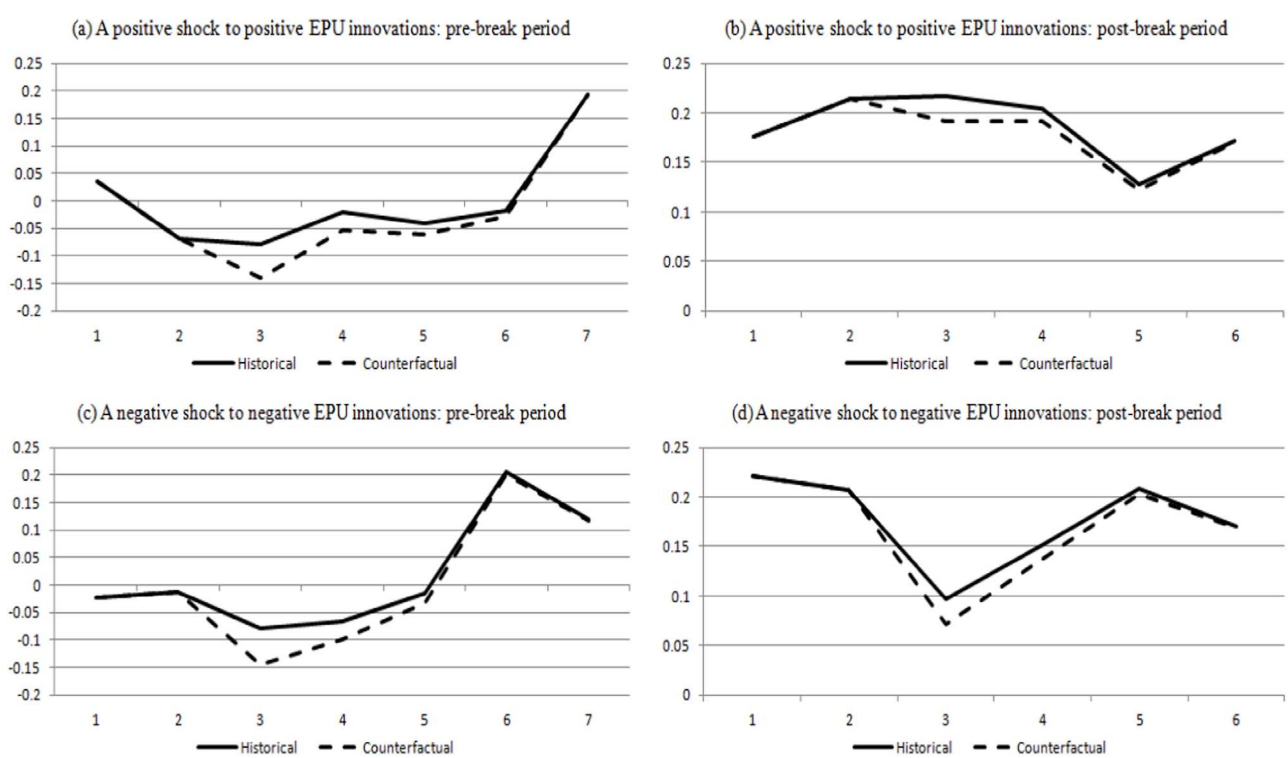

Fig. 15. Implications of transitory US EPU shocks for the SZB-S & P500 correlation.

question. In fact, the above discussions on the four figures also contain the information about the economic significance of the initial correlation impact of a US EPU shock. For example, a 1.5-standard-deviation change in EPU innovations could have an effect as large as -0.0972 (associated with the SHB-S & P500 correlation). This is comparable to the impact of a transitory US EPU shock on the stock-bond correlation (See Li et al., 2015).

The analysis so far has been focused on the cases where a shock and EPU innovations it hits are in the same direction (e.g., a *positive* shock to *positive* EPU innovations). One may wonder what if they have opposite directions (e.g., a *negative* shock to *positive* EPU innovations). To address this question but also to preserve space, we only present one figure, Fig. 16, for comparison. Panels (a) and (c) are directly taken from Fig. 12, while Panels (a') and (c') are newly added.

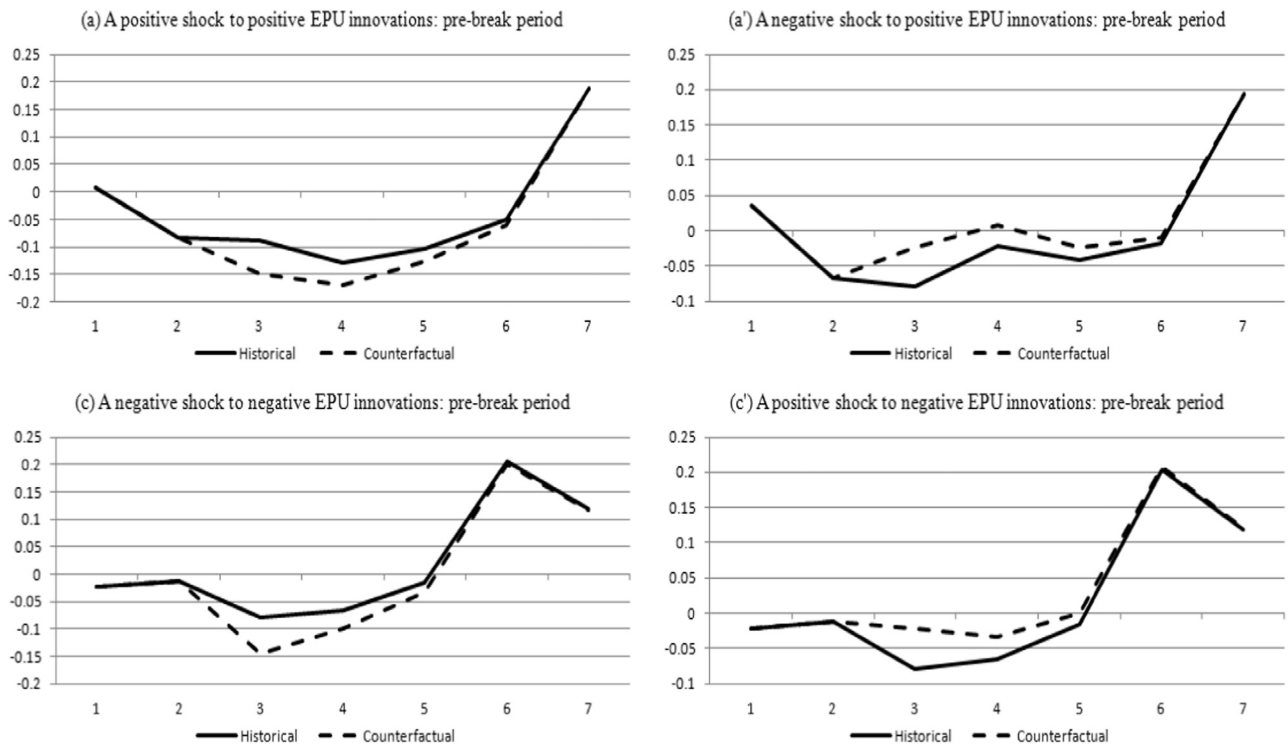

Fig. 16. Implications of transitory US EPU shocks for the SZB-S & P500 correlation: A comparison.

In the latter two panels, we perturb positive EPU innovations by a negative shock, and perturb negative EPU innovations by a positive shock. The two shocks are all equal to 1.5 standard deviation of $\Delta\xi_t$, as in Panels (a) and (c). One can observe that the counterfactual trajectories in Panels (a') and (c') are largely the mirror images of those in Panels (a) and (c). So, our conclusions from Figs. 12–15 should remain unaffected.

4. Conclusions

The focus of this paper is on exploring the linkage between US EPU innovations and four China-US stock market correlations - the SHA-S & P500, the SZA-S & P500, the SHB-S & P500, and the SZB-S & P500 correlation. Serving this purpose, we employ the ADCCX model that incorporates the EPU innovations as an exogenous variable, and estimate the model with and without structural change.

Our efforts have delivered important results. It is the absolute changes in the US EPU index that have a negative impact on the correlations. For example, a larger rise or a larger fall in US policy uncertainty would both reduce the magnitude of subsequent co-movements between the Chinese and American stock markets. And, everything else constant, the reduction in the co-movements is the same across the rise and the fall in US EPU. These findings are robust to the asymmetric effects of non-EPU shocks, to a break in the correlation structure associated with China's QFII reform, and to the four different Chinese stock markets investigated. The results provide the first EPU evidence for stock-stock correlations in the international context, and are complementary to the existing EPU evidence for stock-bond correlations within a country. The results imply that changes in US EPU may affect mainly the purchases/sales in the US stock market, whereby leading to changes in the co-movements of the Chinese stock markets with the US stock market.

Investors whose global market portfolios comprise both Chinese and US stocks or stock indexes may draw an implication of our results for financial risk management. A rise or a fall in the China-US stock market correlations due to changes in US policy uncertainty requires rebalancing of their portfolios by increasing or reducing the weights attached to the Chinese and/or US stock markets. In other words, for gaining diversification benefits, investors need to pay close attention to US policy uncertainty and act accordingly.

It would be of interest to examine which EPU, Chinese or US, is more influential, or whether they would jointly impact, on the China-US stock market co-movements. Investigating these issues would require the use of more and better data (e.g., higher-than-monthly-frequency data) on the Chinese EPU index. We leave these issues for future research when required data become available.

Appendix A

In Section 3 of the paper, we report and discuss the results regarding the SHA-S & P500 and the SZA-S & P500 correlations. The data on the SHA and SZA indexes are denominated in the Chinese yuan, while the data on the S & P500 index in the US dollar. In other words, the potential effects of the yuan-dollar exchange rate, which has become managed floating since July 21, 2005, are ignored. One natural question arises: If taking into account the exchange rate effects, would our results reported in the paper be altered qualitatively? To address this concern, one way is to use a common currency, either the yuan or the dollar. We choose to convert the dollar value of the S & P500 index into Chinese currency.

To save space, we only present Tables A1 and A2 which are similar to Tables 4 and 5 in the paper. It is observed that the estimates of η_E^+ and η_L^+ are negative, while the estimates of η_E^- and η_L^- are positive, at a higher than 1% significance level, consistent with Panels A and B in Table 4. We then impose the restrictions $\eta_E^+ = -\eta_E^-$ (for the pre-break period) and $\eta_L^+ = -\eta_L^-$ (for the post-break period), and test this joint hypothesis. The two

Table A1
Estimation of the ADCCX model with structural change in all parameters.

Panel A SHA vs. S & P500							
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.1386**	0.9907***	0.5353**	0.1987	0.8518***	0.2770	-0.0915***	0.1356***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.1269**	0.9925***	-0.2688**	0.3309***	0.6600***	0.9634***	-0.0641***	0.0560***
LLF = -5871.71.							
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT*= 1.80. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=14.42***						.	
Panel B SZA vs. S & P500							
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E^+	η_E^-
0.0968***	0.9946***	0.5002**	0.3210***	0.5860***	0.3510	-0.0387***	0.0120***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L^+	η_L^-
0.1234***	0.9929***	-0.2674***	0.3595***	0.6097***	0.9553***	-0.0808***	0.0275***
LLF= -5922.12.							
H_0: $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$; H_1: $\eta_E^+ \neq -\eta_E^-$ and/or $\eta_L^+ \neq -\eta_L^-$. *LRT* =1.98. H_0: $\eta_E^+ = \eta_E^-$ and $\eta_L^+ = \eta_L^-$; H_1: $\eta_E^+ \neq \eta_E^-$ and/or $\eta_L^+ \neq \eta_L^-$. *LRT*=12.01***						.	

Note. Both SHA and SZA are yuan-denominated, and S & P500 is converted to become yuan-denominated too. *LLF* is the value of the log likelihood function when maximised. *LRT* denotes the log likelihood ratio test statistic. The reported estimates of η^+ and η^- are multiplied by 100.
*** Significance at the 1% level.
** Significance at the 5% level.

Table A2
Re-estimation of the ADCCX model in Table 4 with restrictions $\eta_E^+ = -\eta_E^-$ ($= \eta_E$) and $\eta_L^+ = -\eta_L^-$ ($= \eta_L$) imposed.

Panel A SHA vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1382***	0.9911***	0.5358***	0.1987*	0.8518***	0.3024	-0.1361***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.1267*	0.9925***	-0.2688**	0.3309***	0.6600***	0.9634***	-0.0684***
LLF = -5872.61. $\bar{\rho}$ = -0.0064. $\bar{\rho}_E$ = -0.0539. $\bar{\rho}_L$ = 0.0398.						
Panel B SZA vs. S & P500						
α_{1E}	β_{1E}	γ_{1E}	α_{2E}	β_{2E}	γ_{2E}	η_E
0.1062***	0.9944***	0.4129***	0.2982***	0.5860***	0.3558***	-0.0185***
α_{1L}	β_{1L}	γ_{1L}	α_{2L}	β_{2L}	γ_{2L}	η_L
0.0939	0.9908***	-0.1739**	0.3587***	0.5801	0.9753**	-0.0457***
LLF = -5923.11. $\bar{\rho}$ = 0.0336. $\bar{\rho}_E$= -0.0786. $\bar{\rho}_L$= 0.1417.						

Note: Both SHA and SZA are yuan-denominated, and S & P500 is converted to become yuan-denominated too. *LLF* is the value of the log likelihood function when maximised. *LRT* denotes the log likelihood ratio test statistic. The reported estimates of η^+ and η^- are multiplied by 100. $\bar{\rho}$, $\bar{\rho}_E$ and $\bar{\rho}_L$ are unconditional correlations over, respectively, the whole sample period, the pre-break sample period and the post-break sample period. *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. The last two terms in Eq. (4) now become $\eta_E^+\Delta\xi_{t-1}^+ + \eta_E^-\Delta\xi_{t-1}^- = \eta_E|\Delta\xi_{t-1}|$ over the pre-break period, and $\eta_L^+\Delta\xi_{t-1}^+ + \eta_L^-\Delta\xi_{t-1}^- = \eta_L|\Delta\xi_{t-1}|$ over the post-break period.

corresponding LRT statistics in Table A1 (*LRT* = 1.80 in Panel A; and *LRT* = 1.98 in Panel B) do not allow us to reject the joint null, for the two correlations. Furthermore, we test the restrictions $\eta_E^+ = \eta_E^-$ (for the pre-break period) and $\eta_L^+ = \eta_L^-$ (for the post-break period). The two corresponding LRT statistics in Table A1 (*LRT* = 14.42 in Panel A; and *LRT* = 12.01 in Panel B) allow us to decisively reject the joint null, as they are statistically significant at a higher than 1% level.

We then re-estimate the ADCCX model while imposing the restrictions $\eta_E^+ = -\eta_E^-$ and $\eta_L^+ = -\eta_L^-$ as suggested by the test results in Table A1. Table A2 summarises the results. One can see that the estimates of η_E and η_L are all negative at the 1% level for the two correlations. It can now be concluded, therefore, that allowing for the yuan-dollar exchange rate effects does not alter our results for the two correlations reported in the paper.

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