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## Article

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Article

# Financial Contagion: A Tale of Three Bubbles

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**Abstract:** The primary purpose of the study is to identify and measure the properties of asset bubbles, volatility clustering, and financial contagion during three recent financial market anomalies that originated in the U.S. and Chinese markets. In particular, we focus on the 2000 DotCom Bubble, the 2008 Housing Crisis, and the 2015 Chinese Bubble. We employ three main empirical methods; the LPPL model to identify asset bubbles, the DCC-GARCH model to measure volatility clustering, and the Diebold-Yilmaz volatility spillover index to measure the level of financial contagion. We provide robust evidence that during the DotCom bubble there was very limited spillover between the S&P 500, the Shanghai, and the Shenzhen Composite Indexes. However, there was significantly more spillover effects in the two more recent crises, i.e., the Housing crisis and the 2015 Chinese Bubble. Together, these results highlight the fact that as financial markets have become more globalized, there are greater levels of volatility transmission and correspondingly fewer potential benefits from international diversification.

**Keywords:** financial contagion; volatility clustering; spillover effects; bubble



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## 1. Introduction

Asset bubbles, volatility clustering, and financial contagion have long been of interest to researchers, market participants, and regulators. Prior research has largely focused on each of these phenomena separately, with little focus on examining them within a unified framework. Our main goal in this paper is to fill the void in the literature by investigating the dynamic correlation and contagion between notable economic bubbles in two major economies, i.e., the U.S. and Chinese stock markets. The increase in globalization led to markets being more interconnected. In our first two research questions, we investigate whether there was an increase in the level of volatility persistence and spillover during three recent major bubbles: the Dot-Com Bubble of 1995–2001, the Housing Bubble of 2008, and the Chinese equity bubble of 2014–2015. Since prior literature confirms that an additional source of risk in financial markets is the degree of variability in volatility (see for example Agarwal et al. 2017), with our third research question, we investigate whether there was an increase in the volatility of volatility (hereafter vol of vol) in each of these markets, during each bubble.

Using daily data on the S&P 500 Index, the SSE Composite Index (Shanghai), and the SZSE Composite Index (Shenzhen), we make at least four important contributions to the literature. First, we show that the U.S. and Chinese stock markets have had an evolving relationship during times of financial turbulence, but the volatility clustering effect between the two markets has been consistently elevated. Second, we provide empirical evidence on the evolution of the vol of vol of each market during each of the bubbles. Our results confirm that the Chinese indexes exhibit high vol of vol during the Dot-Com Bubble, but the S&P 500 maintained relatively low vol of vol in that period. In the case of the Housing Bubble, both U.S. and Chinese equity markets experienced low vol of vol, while in the more

recent Chinese Bubble, the Chinese indexes exhibit little vol of vol, while the S&P 500 had elevated vol of vol. To the best of our knowledge, this is the first study to investigate the vol of vol in each of these markets during each of these financial crises. These results are important for market participants who are concerned with hedging the risk of increased volatility.

In our third contribution, we show that the initiation and conclusion (popping) of asset bubbles can be empirically simulated through the volatility clustering process. Our results suggest that the Log Periodic Power Law (LPPL) model of [Brée and Joseph \(2013\)](#) is capable of accurately identifying a bubble period. Fourth, using the model of [Diebold and Yilmaz \(2009, 2012\)](#), we quantify the level of spillover between each market during each of these crises. Our results reveal that the S&P 500 is having a lower spillover effect to the Chinese markets, while Shenzhen's effect is gradually increasing, especially in the post-Housing Bubble period. Our results on the spillover effect from the U.S. market is consistent with the finding of [Bekaert et al. \(2014\)](#), who also document only weak evidence of transmission from U.S. equity markets to other countries during the Housing Bubble. However, our finding on the increasing spillover effect from the Shenzhen market is novel and highlights the important shifts in volatility transmission during this most recent financial crisis.

## 2. Related Literature and Hypotheses Development

Previous research into what features constitute a “bubble” is highly subjective and often conflicting.<sup>1</sup> Historically, financial bubbles are generated when the market value of an index or asset class far exceeds the actual intrinsic value. Per [Case and Shiller \(2003\)](#), a bubble is a market situation where irrational investor expectations of future price increases cause current prices to be unjustifiably elevated. However, in analyzing any (supposed) bubble, it is important to consider the impact of governmental and economic policy on equity markets. For example, a shift in policy can also shift the benchmark for a market anomaly to be correctly designated as an asset bubble. This phenomenon is referred to as “process switching” ([Flood and Hodrick 1986](#)), which presents investors a more nuanced perspective of fundamental economic conditions.<sup>2</sup>

### 2.1. The Dot-Com Bubble

According to Robert [Shiller \(2000\)](#), various bubbles are largely due to a populist assumption of supposed “new eras” in an economy. New eras are investor beliefs that markets have been permanently altered by some underlying factor or trend, even though the structure of these markets have not changed. An Internet mania saw the Nasdaq Composite Index increasing by almost 400% over the 5-years from 1995 to 2000. In fact, “in the two-year period from early 1998 through February 2000, the Internet sector earned over 1000 percent returns on its public equity” ([Ofek and Richardson 2003](#)). However, once this bubble burst, the Nasdaq lost 78% of its value.

### 2.2. The Housing Bubble

The Housing Bubble, which ultimately led to the global financial crisis of 2008, had a more prolonged, detrimental effect on the U.S. macro economy. The new era that the Housing Bubble embodied was far more unprecedented. Rather than asset values being simply skewed away from intrinsic values, there was a major systemic breakdown in the U.S. banking and financial system. Not only were home values and mortgages wildly inflated, but massive subprime lending, combined with increased securitization, led to global economic calamity. According to the S&P/Case-Shiller national home-price index, home prices in the U.S. rose 124% over a 9-year span from 1997 to 2006. Lending institutions took advantage of these astronomical price increases by implementing what some consider reckless practices involving unreasonable leveraging and subprime CDOs. When this bubble burst, the S&P 500 lost approximately 50% of its value. Although the root cause of the Dot-Com and Housing Bubbles are quite different, the global impact from the deconstruction of both market events was similar in their scope. A large number of studies

have investigated contagion during this period (see for example, [Wang et al. 2017](#); [Jin and An 2016](#); [Dimitriou et al. 2013](#)).

### 2.3. The 2015 Chinese Bubble

The U.S. and Chinese economies have become more integrated over recent history ([Johansson 2010](#)). A major theoretical reason for possible co-movements in Chinese and U.S. equity markets relates to the Chinese legislation of the Qualified Foreign Institutional Investor (QFII) and Qualified Domestic Institutional Investor (QDII) programs. The QFII was passed in 2002 and allowed certain international investors access to A-shares in the Shanghai and Shenzhen stock exchanges, while the QDII was passed in 2008 and allowed Chinese investors to invest in U.S. equity indexes. Accordingly, a bilateral exchange was created for U.S. and Chinese financial trading. However, with the liberalization of markets in a communist regime, a more *laissez faire* approach is introduced and the existing relation between macroeconomic data and variables may be drastically altered ([Lucas 1976](#)). This shift in control would eventually play an integral role in the 2015 Chinese market bubble.

Between June 2014 and June 2015, the Shanghai index appreciated by approximately 150%, while the Shenzhen index increased by about 190%. A primary reason for this sudden bubble within these Chinese stock indexes was the implementation of margin trading in Chinese equities ([Song 2020](#)). With this new infusion of debt and leverage in the Chinese stock markets, the Shanghai and Shenzhen exchanges were propped up in value. When this bubble burst, the results were more devastating than could be imagined, \$2.6 trillion of the Shanghai and Shenzhen indexes was eroded ([Zeng et al. 2016](#)). During this period, market volatility skyrocketed and stock indexes across the globe plummeted.

### 2.4. Financial Contagion and Volatility Persistence

[Forbes and Rigobon \(2002\)](#) define contagion as a significant increase in cross-market dynamic correlations over a certain period, in contrast to interdependence, defined as when markets have a strong dynamic correlation consistently over time. [Bekaert et al. \(2014\)](#) investigate transmission of the crisis from the U.S. to the equity markets of 415 countries during the Housing Bubble and find only weak evidence for international contagion from U.S. equity markets. In contrast, [Chiang and Wang \(2011\)](#) find evidence of volatility of volatility transmission from the U.S. to some G7 countries during the housing crisis. [BenMim and BenSaïda \(2019\)](#) also report significant contagion between the U.S. and countries in the Eurozone during crises periods. Similarly, [Gomez-Gonzalez et al. \(2018\)](#) document transmission of the housing bubble from the U.S. mostly to European countries.

Whereas most of the extant literature focus on a single bubble period, we consider multiple bubble periods. Furthermore, while most of the prior studies focus on bubbles that originate in the U.S. or European stock markets, we extend the literature by investigating a bubble that originated in the Chinese economy. The S&P 500 index experienced a marked increase in volatility immediately preceding the crash of the Housing Bubble, while the Shanghai and Shenzhen indexes had marked decreases in volatility during the same period ([Sornette et al. 2018](#)). However, even with these fluctuations in historical volatility, the volatility persistence could still maintain an elevated level. For example, the dynamic nature of contagion can cause an increase in the autocorrelation of market volatility with large price changes following large price changes and small price changes following small price changes. These patterns in price fluctuations cause a cluster effect, with the interlinked, forecastable volatility present in the markets, otherwise known as volatility clustering ([Mandelbrot 1963](#)).

We examine the recent Chinese market turmoil, as well as the Dot-Com and Housing Bubbles, to establish whether there is contagion of volatility cluster over the course of Chinese market liberalization. The study that is most closely related to ours is that of [Imran Yousaf et al. \(2020a\)](#) who investigate return and volatility transmission from the U.S. and Chinese markets to countries in Latin America during the housing bubble and the Chinese crises. However, they do not investigate transmission between the U.S. and

Chinese markets. They also acknowledge the need to reexamine these market linkages using other econometric models, as we do in this study. Unlike their study and others that investigate economic bubbles, financial contagion, and volatility clustering independently, our study provides a combined view of the evolving relation between these three elements.

### 3. Data and Empirical Methods

#### 3.1. Data and Descriptive Statistics

We collect daily levels of the S&P 500 Index, the SSE Composite Index (Shanghai), and the SZSE Composite Index (Shenzhen) from Bloomberg. We use the period from 4 January 1995 to 30 November 2004 for the Dot-Com Bubble; from 1 December 2004 to 16 March 2009 for the Housing Bubble; and from 5 May 2014 to 15 September 2015 for the 2015 Chinese Bubble.<sup>3</sup> The starting and ending points for the Dot-Com and Housing Bubble samples are based on [Bekaert et al. \(2014\)](#) and [Lin et al. \(2014\)](#). We estimate the period of the 2015 Chinese Bubble by fitting the volatility-confined LPPL model to the data. We provide details of the model in Section 3.2.

#### 3.2. Log Periodic Power Law (LPPL) Model

We use the Log Periodic Power Law (LPPL) model of [Brée and Joseph \(2013\)](#) to empirically test for the constitution of an asset bubble. The model is given as:

$$\log (y_t) = A + B (t_c - t)^m \{1 + C \cos (\omega \log (t_c - t) + \varphi)\} \quad (1)$$

where  $\log (y_t) > 0$  is the log of the index at time  $t$ ,  $A > 0$  is the value that  $\log y_t$  would have if the bubble were to last until the critical time  $t_c$ ,  $B < 0$  is the decrease in  $y_t$  over the time unit before the crash if  $C$  is close to zero,  $C$  is the magnitude of the fluctuations around the exponential growth, as a proportion,  $t_c > 0$  is the critical time,  $t < t_c$  is any time into the bubble, preceding  $t_c$ ,  $m$  is the exponent of the power law growth,  $\omega$  is the frequency of the fluctuations during the bubble, and  $\varphi$  is a shift parameter.

The parameters of the LPPL econophysics approach have been widely employed as theoretical indicators of speculative market bubbles and as precursors to subsequently ensuing market crashes ([Zhang et al. 2016](#)). In theory, if a stock index conforms to the price power law acceleration and log periodic oscillations as stipulated by the LPPL model, a market crash would be considered as very likely ([Brée and Joseph 2013](#)). In this study we use a variant of the LPPL model, i.e., the volatility-confined LPPL model ([Lin et al. 2014](#)) which is parameterized by the price dynamics:

$$\frac{dI}{I} = \mu(t)dt + \sigma_Y dY + \sigma_W dW - \kappa dj \quad (2)$$

$$dY = -\alpha Y dt + dW \quad (3)$$

The notation  $I$  delineates the stock index and  $W$  represents a standard Weiner process. Time-varying drift leading to price acceleration in a bubble regime, represented by  $\mu(t)$ , is accompanied by a jump process, denoted by  $j$ , which has a value of zero before a bubble crash and a value of one following a bubble crash. For the values  $0 < \alpha < 1$ ,  $Y$  is indicative of an Ornstein-Uhlenbeck or mean-reverting process, where the variables  $dY$  and  $Y$  are stationary. Therefore, the parameters of a volatility-confined bubble are indicative of a bubble regime within the context of GARCH processes.

Appendix A provides details of the calibration of the LPPL model for the 2015 Chinese bubble.

#### 3.3. DCC-GARCH Model

The multivariate DCC-GARCH model ([Engle 2002](#)) can be expressed as follows:

$$r_t = \mu_t + \varepsilon_t \quad (4)$$

where  $r_t$  is log return of the index at time  $t$ ,  $\mu_t$  is expected return of the index and  $\varepsilon_t$ , the error term is independent and identically distributed with mean 0 and variance of 1. The conditional variance-covariance matrix is written as:

$$H_t = D_t R_t D_t \tag{5}$$

where  $R_t$  is the time-varying correlation matrix and  $D_t$  is a diagonal matrix of conditional standard deviations for return series. The conditional correlation matrix is written as:

$$R_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2} \tag{6}$$

where  $(\text{diag}(Q_t))^{-1/2} = \text{diag}\left(\frac{1}{\sqrt{q_{11,t}}}, \dots, \frac{1}{\sqrt{q_{nn,t}}}\right)$

The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \tag{7}$$

where  $Q_t = (q_{ij,t})$ .

The conditional correlation at time  $t$  is expressed as:

$$\rho_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}} \quad , \quad i, j = 1, 2, \dots, n, \text{ and } i \neq j \tag{8}$$

The correlation coefficient in the bivariate case is expressed as:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1,t-1}\mu_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}] [(1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]}} \tag{9}$$

The DCC-GARCH model is a forecasting model that quantifies volatility persistence for a sample period, while also providing dynamic correlation coefficients for the same period. We estimate the parameters using the maximum log-likelihood method which separates the equation into a function of variances and a function of correlations (Engle 2002).

### 3.4. Diebold-Yilmaz Volatility Spillover Index

The Diebold-Yilmaz volatility spillover index (Diebold and Yilmaz 2012) acts as an extension of a variance decomposition for a conventional VAR framework. Cross variance shares, or spillovers, are fractions of H-step-ahead error variances in projecting  $x_i$  with original shocks to  $x_j$  for  $i, j = 1, 2, \dots, N$  such that  $i \neq j$ . The subscripts of  $i$  and  $j$  in the spillover index denote the dependent and explanatory variables in the model, respectively. For example, when the S&P 500 Index is  $i$ , the SSE (or SZSE) would be  $j$ , etc. The H-step-ahead forecast error variance decompositions by  $\theta_{ij}^s(H)$  for  $H = 1, 2, \dots$ , is given by:

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

where  $\Sigma$  is the variance matrix for the error vector  $\varepsilon$ ,  $\sigma_{jj}$  is the standard deviation of the error term for the  $j$ th equation, and  $e_i$  is the selection vector, with one as the  $i$ th element and zeros otherwise. As was explained, the sum of the elements in each row of the variance decomposition table is not equal to 1:  $\sum_{j=1}^N \theta_{ij}^s(H) \neq 1$ . For the purposes of properly converting the variance decomposition matrix to the spillover index, each entry of the variance decomposition matrix is normalized by the row sum as:

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

By construction  $\sum_{j=1}^N \tilde{\theta}_{ij}^s(H) = 1$  and  $\sum_{i,j=1}^N \tilde{\theta}_{ij}^s(H) = N$ .

The total Diebold-Yilmaz volatility spillover index is then denoted by:

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

The Diebold-Yilmaz spillover index acts as a gauge of volatility spillover, or volatility contagion.<sup>4</sup>

#### 4. Results

Table 1 provides descriptive statistics of returns on the S&P 500, the Shanghai (SSE), and the Shenzhen (SZSE) Composite Indexes for each of the Bubble periods. Panel A provides results for the full period of the Dot-Com Bubble, and Panels B and C provide similar results for the Housing Bubble and the 2015 Chinese Bubble, respectively. In Panel A we also analyze sub-periods corresponding to the Build-Up, Bubble and Crash periods of the Dot-Com Bubble, and in Panel B we further analyze the Build-Up and Crash sub-periods of the Housing Bubble. The sample period for each respective bubble is: the Dot-Com Bubble, from 4 January 1995 to 30 November 2004; the Housing Bubble from 1 December 2004 to 16 March 2009; and the Chinese Bubble from 5 May 2014 to 15 September 2015.

**Table 1.** Descriptive Statistics of Returns Series.

Panel A: Dot-Com Bubble												
	Full Bubble period			Build-Up period			Bubble period			Crash period		
	S&P 500	SSE	SZSE	S&P 500	SSE	SZSE	S&P 500	SSE	SZSE	S&P 500	SSE	SZSE
Mean	0.041	0.032	0.039	0.096	0.126	0.217	0.081	0.057	0.039	−0.015	−0.033	−0.051
Median	0.058	0.018	0.056	0.090	0.017	0.273	0.092	0.044	0.016	0.004	0.001	0.016
Std. Dev.	1.182	1.924	2.011	0.691	2.858	2.892	1.315	1.810	1.986	1.271	1.330	1.395
Kurtosis	3.203	23.632	17.069	3.232	18.723	14.614	3.637	4.208	4.074	1.656	6.273	5.775
Skewness	−0.066	0.923	0.307	−0.193	1.187	0.486	−0.294	−0.435	−0.572	0.169	0.667	0.407
Minimum	−7.113	−17.905	−18.887	−3.131	−17.905	−18.887	−7.113	−9.246	−10.172	−5.047	−6.543	−6.817
Maximum	5.574	26.993	24.904	3.761	26.993	24.904	5.402	8.665	8.682	5.574	9.401	9.244
N	2311	2311	2311	523	523	523	741	741	741	1047	1047	1047
Panel B: Housing Bubble												
	Full Bubble period			Build-Up period			Crash period					
	S&P 500	SSE	SZSE	S&P 500	SSE	SZSE	S&P 500	SSE	SZSE			
Mean	−0.044	0.046	0.071	0.031	0.195	0.216	−0.169	−0.202	−0.172			
Median	0.070	0.137	0.243	0.083	0.207	0.308	0.008	−0.126	−0.008			
Std. Dev.	1.575	2.127	2.264	0.711	1.701	1.841	2.399	2.676	2.817			
Kurtosis	14.797	3.407	2.775	2.336	4.356	3.661	5.730	1.817	1.298			
Skewness	−0.748	−0.402	−0.601	−0.537	−0.601	−0.606	−0.400	−0.116	−0.404			
Minimum	−13.799	−12.764	−12.697	−3.534	−9.256	−8.930	−13.799	−12.764	−12.697			
Maximum	10.957	9.034	8.515	2.134	7.890	8.351	10.957	9.034	8.515			
N	1005	1005	1005	628	628	628	377	377	377			
Panel C: 2015 Chinese Bubble												
	Full Bubble period											
	S&P 500	SSE	SZSE									
Mean	0.015	0.120	0.129									
Median	0.042	0.179	0.475									
Std. Dev.	0.849	2.123	2.231									
Kurtosis	3.306	3.667	2.539									
Skewness	−0.382	−0.977	−1.098									
Minimum	−4.021	−8.873	−8.195									
Maximum	3.829	6.040	5.259									
N	327	327	327									

Table 2 shows the correlations between daily returns on the three indices for each of the respective Bubble periods and respective sub-periods.

**Table 2.** Correlations between Return Series.

<b>Panel A: Dot-Com Bubble</b>								
	Full Bubble period		Build-Up period		Bubble period		Crash period	
	S&P 500	SSE	S&P 500	SSE	S&P 500	SSE	S&P 500	SSE
SSE	−0.0332		−0.1038		−0.0452		0.0027	
SZSE	−0.0290	0.8983	−0.1309	0.8253	−0.0262	0.9618	0.0094	0.9759
<b>Panel B: Housing Bubble</b>								
	Full Bubble period		Build-Up period		Crash period			
	S&P 500	SSE	S&P 500	SSE	S&P 500	SSE	S&P 500	SSE
SSE	0.0495		0.0864				0.0341	
SZSE	0.0190	0.9285	0.0680	0.9303			−0.0024	0.9266
<b>Panel C: 2015 Chinese Bubble</b>								
			Full Bubble period					
			S&P 500		SSE			
SSE			0.2024		0.8335			
SZSE			0.1827					

We calibrate the LPPL model using non-linear least squares and a Levenberg-Marquardt algorithm (LMA) (Liberatore 2010) to project the logarithmic oscillations of the log returns for the Shanghai and Shenzhen indexes. The purpose of the LMA is to reduce the standard residual error from the exponential non-linear squares initial solutions to a non-convex optimization for LPPL fitting. Essentially, a major reduction of residual standard error from the initial solutions signifies a bubble (LPPL) process, while no major reduction is simply an indicator of exponential growth in an index.

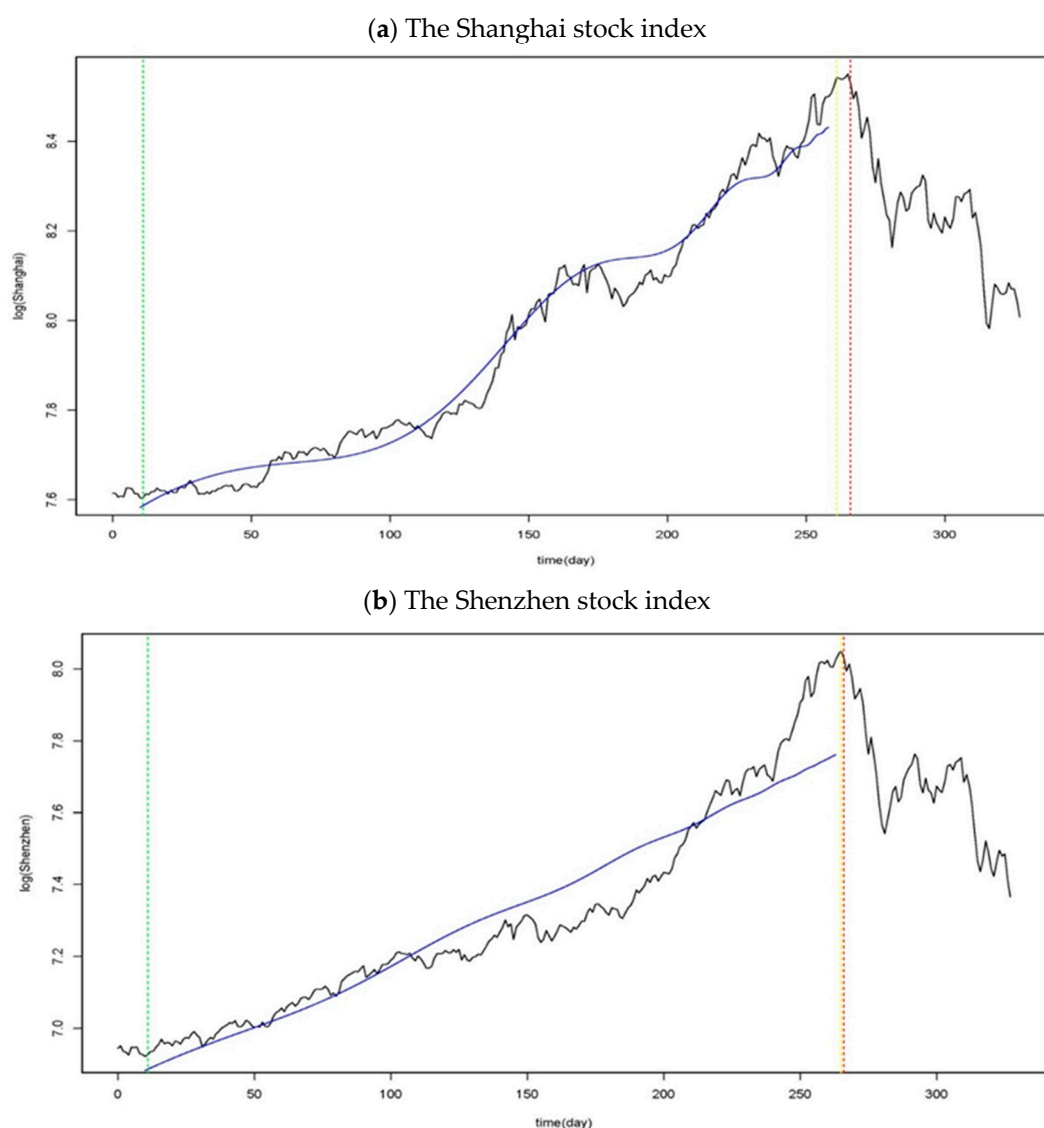
Table 3 provides results of our LPPL calibration of the 2015 Chinese Bubble. The time parameters are  $t_{start}$ ,  $t_{end}$ , and  $t_c$ , which represent the first date in our data, the final date in our data and the estimate of the critical date, respectively. The other parameters of the model are  $m$ , the exponent of the power law growth,  $\omega$ , the frequency of the fluctuations during the bubble,  $\phi$ , the shift parameter, and  $A$ ,  $B$ , and  $C$ , which are the value of  $\log y_t$  if the bubble lasts until the critical time, the decrease in  $\log y_t$  over the number of days until the bubble bursts, and the magnitude of the fluctuations around the exponential growth, respectively.

**Table 3.** 2015 Chinese Bubble LPPL Calibration.

	$t_{start}$	$t_{end}$	$t_c$	$m$	$\omega$	$\phi$	$A$	$B$	$C$
SSE	5 May 2014	15 September 2015	3 June 2015	0.941	7.387	−2.106	8.436	−0.004	0.126
SZSE	5 May 2014	15 September 2015	10 June 2015	0.975	10.821	−16.420	7.765	−0.004	0.021

Panel a of Figure 1 shows the Shanghai stock index and Panel b of Figure 1 shows the Shenzhen index from 5 May 2014 to 15 September 2015. The green line shows the minimum value, the red line is the maximum value, and the yellow line indicates the computed initial critical time.





**Figure 1.** LPPL model calibration for: (a) The Shanghai stock index and (b) The Shenzhen stock index

The results in Table 3 and Figure 1 indicate that while the Shanghai index conforms to mean-reverting, the LPPL bubble regime reveals that the Shenzhen index adheres to strict exponential growth. The disparity between the two Chinese indexes in volatility-confined LPPL bubble further supports the notion that volatility clustering is an inconsistent indicator of bubble contagion between the two countries. Differing results in this case reveal that volatility clustering between these two indexes mirror one another, but the log return series are disparate. Viewing contagion through the lens of volatility once again provides a completely different perspective than simply analyzing contagion through return or price movement correlations, even with only the Chinese indexes in a relatively localized Chinese bubble.

The data is made synchronous and stationary between stock indices by calculating the first log difference of the returns and synchronizing sample period dates across indices. The GARCH assumption of  $1 > (\alpha + \beta)$  is violated several times, indicating potential explosive processes.

Table 4 provides GARCH estimates for each of our return series in each of the bubble periods and sub-periods. In Panels A–D we provide results for the full period, the Build-Up, Bubble and Crash periods of the Dot-Com Bubble, in Panels E–G we provide similar results for the Housing Bubble, and in Panel H we provide results for the full-sample of the 2015 Chinese Bubble. The sample period for each respective bubble is: the Dot-Com Bubble,

from 4 January 1995 to 30 November 2004; the Housing Bubble from 1 December 2004 to 16 March 2009; and the Chinese Bubble from 5 May 2014 to 15 September 2015.

**Table 4.** GARCH Estimates.

<b>Panel A: Dot-Com Bubble—Full Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	$\alpha$	B	A	$\beta$
0.0717 ***	0.9243 ***	0.1209 ***	0.8898 ***	0.1275 ***	0.8765 ***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<b>Panel B: Dot-Com Bubble—Build-Up Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	$\alpha$	$\beta$	A	$\beta$
0.0354 *	0.9529 ***	0.1285 **	0.4773 ***	0.1766 **	0.494 ***
(0.069)	(0.000)	(0.033)	(0.000)	(0.011)	(0.000)
<b>Panel C: Dot-Com Bubble—Mid-Bubble Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	$\alpha$	$\beta$	$\alpha$	$\beta$
0.0922 *	0.7957 ***	0.1812 **	0.7695 ***	0.2082 ***	0.7195 ***
(0.091)	(0.000)	(0.034)	(0.000)	(0.003)	(0.000)
<b>Panel D: Dot-Com Bubble—Crash Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	A	$\beta$	$\alpha$	$\beta$
0.0866 ***	0.9047 ***	0.1538 ***	0.8041 ***	0.1583 ***	0.8121 ***
(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
<b>Panel E: Housing Bubble—Full Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	A	$\beta$	$\alpha$	$\beta$
0.0971 ***	0.8985 ***	0.0496 ***	0.9498 ***	0.0522 ***	0.9458 ***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<b>Panel F: Housing Bubble—Build-Up Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	A	$\beta$	$\alpha$	$\beta$
0.0485 ***	0.8828 ***	0.0716 ***	0.9243 ***	0.0717 ***	0.9215 ***
(0.004)	(0.000)	(0.002)	(0.000)	(0.006)	(0.000)
<b>Panel G: Housing Bubble—Crash Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	A	$\beta$	$\alpha$	$\beta$
0.1220 ***	0.8750 ***	0.0238	0.8791 ***	0.0240	0.9476 ***
(0.000)	(0.000)	(0.471)	(0.000)	(0.322)	(0.000)
<b>Panel H: 2015 Chinese Bubble—Full Period</b>					
<i>S&amp;P 500</i>		<i>SSE</i>		<i>SZSE</i>	
$\alpha$	$\beta$	A	$\beta$	$\alpha$	$\beta$
0.2206 ***	0.6594 ***	0.1634 ***	0.8548 ***	0.1096 ***	0.8942 ***
(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)

Note: \*, \*\*, \*\*\* denotes significance at the 10%, 5% and 1%, respectively.

Generally, the higher the  $\alpha$  (lagged squared unexpected returns) coefficient and the lower the  $\beta$  (lagged return variance) coefficient, volatility-of-volatility is presumed to be more elevated. As an example, the GARCH estimates indicate that the  $\alpha$  coefficient is statistically insignificant for the S&P 500 during the buildup and continuation of the Dot-Com Bubble, implying stable volatility. The results also show that the  $\alpha$  coefficient for the Shanghai and Shenzhen indexes during the Housing Bubble crash is insignificant. Both

the  $\alpha$  and  $\beta$  coefficients are statistically significant for the Chinese indexes throughout the 2015 Chinese Bubble, this indicates explosive processes during this period.

Table 5 provides DCC estimates for each of the bubbles investigated. In Panels A–D we provide results for the full period, the Build-Up, Bubble and Crash periods of the Dot-Com Bubble, in Panels E–G we provide similar results for the Housing Bubble and in Panel H we provide results for the full-sample of the 2015 Chinese Bubble. The sample period for each respective bubble is: the Dot-Com Bubble, from 4 January 1995 to 30 November 2004; the Housing Bubble from 1 December 2004 to 16 March 2009; and the Chinese Bubble from 5 May 2014 to 15 September 2015.

**Table 5.** DCC Estimates.

<b>Panel A: Dot-Com Bubble-Full Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0046 *** (0.000)	−0.9683 *** (0.000)	−0.0002 N/A	0.7854 N/A
<b>Panel B: Dot-Com Bubble—Build-Up Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0126 (0.344)	0.8999 *** (0.000)	0.0147 (0.390)	0.8928 *** (0.000)
<b>Panel C: Dot-Com Bubble—Mid-Bubble Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
−0.0106 *** (0.008)	1.0003 *** (0.000)	−0.0227 *** (0.004)	0.9161 *** (0.000)
<b>Panel D: Dot-Com Bubble—Crash Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
−0.0016 *** (0.000)	1.0402 *** (0.000)	0.0362 (0.384)	−0.1231 (0.867)
<b>Panel E: Housing Bubble—Full Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0115 (0.326)	0.9498 *** (0.000)	0.0090 (0.664)	0.8650 * (0.057)
<b>Panel F: Housing Bubble—Build-Up Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0136 (0.733)	0.5674 (0.539)	−0.0021 (0.915)	0.8499 (0.267)
<b>Panel G: Housing Bubble—Crash Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0373 (0.262)	0.8639 *** (0.000)	0.0496 (0.299)	0.7606 *** (0.001)
<b>Panel H: 2015 Chinese Bubble—Full Period</b>			
<i>S&amp;P 500-SSE</i>		<i>S&amp;P 500-SZSE</i>	
a	B	a	b
0.0732 (0.121)	0.7393 *** (0.000)	0.0277 (0.347)	0.8889 *** (0.000)

Note: \*, \*\*\* denotes significance at the 10% and 1%, respectively.

The DCC estimates in Table 5 show that the volatility persistence in the indices varies in a cyclical manner as the three bubbles progress, but there is little to no consistency in the dynamic conditional correlations for the log return series. However, it is important to note that the dynamic conditional correlations are more helpful in analyzing returns or price contagion, rather than volatility contagion which we investigate using the Diebold-Yilmaz volatility spillover index.

Table 6 provides volatility spillover results using the model of Diebold and Yilmaz (2012) for each of the bubbles we investigate. In Panel A we provide results for the full period of the Dot-Com Bubble, and in Panels B and C we provide similar results for the Housing Bubble and the 2015 Chinese Bubble, respectively. The sample period for each respective bubble is: the Dot-Com Bubble, from 4 January 1995 to 30 November 2004; the Housing Bubble from 1 December 2004 to 16 March 2009; and the Chinese Bubble from 5 May 2014 to 15 September 2015.

**Table 6.** Volatility Spillover Results.

<b>Panel A: Dot-Com Bubble</b>				
	<i>S&amp;P 500</i>	<i>SSE</i>	<i>SZSE</i>	<b>From Others</b>
<i>S&amp;P 500</i>	99.6	0.4	0.0	0.4
<i>SSE</i>	0.4	99.2	0.4	0.8
<i>SZSE</i>	0.3	79.6	20.2	79.8
Contribution to others	0.6	79.9	0.5	81.0
Contribution including own	100.2	179.1	20.7	27.0%
<b>Panel B: Housing Bubble</b>				
	<i>S&amp;P 500</i>	<i>SSE</i>	<i>SZSE</i>	<b>From Others</b>
<i>S&amp;P 500</i>	97.9	2.1	0.0	2.1
<i>SSE</i>	3.5	96.0	0.4	4.0
<i>SZSE</i>	2.8	81.8	15.4	84.6
Contribution to others	6.3	83.9	0.5	90.7
Contribution including own	104.2	179.9	15.9	30.2%
<b>Panel C: 2015 Chinese Bubble</b>				
	<i>S&amp;P 500</i>	<i>SSE</i>	<i>SZSE</i>	<b>From Others</b>
<i>S&amp;P 500</i>	91.1	8.7	0.2	8.9
<i>SSE</i>	2.5	95.6	1.9	4.4
<i>SZSE</i>	4.2	72.8	22.9	77.1
Contribution to others	6.7	81.5	2.2	90.5
Contribution including own	97.8	177.1	25.1	30.2%

The results of the Diebold-Yilmaz volatility spillover index in Table 6 provide a more accurate gauge of the volatility transmission and contagion that occur between the U.S. and Chinese indexes from bubble-to-bubble. The overall volatility spillover during the Dot-Com Bubble is negligible, but the spillover during the Housing Bubble and the 2015 Chinese Bubbles is highly significant, albeit the internal components have shifted. The spillover from the S&P 500 is reducing over time while the Shenzhen's effect gradually increases. The volatility spillover results provide evidence that the overall volatility spillover effect is being maintained from the Housing Bubble. In other words, the Housing Bubble seems to be a pivotal event for volatility contagion in global markets going forward. This finding suggests that analysis of volatility transmission may need to be altered subsequent to this event.

## 5. Conclusions

In this paper, we use the setting of the three most recent financial crises that originated in the world's two largest economies to show how asset bubbles, volatility clustering and

financial contagion can be reliably identified and measured. Our main research questions are whether there was an increase in volatility persistence, vol of vol and volatility spillover during these times of financial turmoil. We find no significant evidence of a consistent contagion effect between the U.S. and Chinese stock indexes. Although the volatility persistence is high in both stock markets, the correlation coefficients are very unstable. The increase in correlations and overall volatility clustering that exist during the Housing Bubble could be a byproduct of QFII and QDII legislation that have made the Chinese economy less insulated. However, the high volatility of volatility, or “spikiness,” that was characteristic of both the Chinese indexes during the Dot-Com Bubble and the S&P 500 during the 2015 bubble, illustrate that the relationship between these equity markets is still very unpredictable. The cyclicity in the volatility-of-volatility ranging from the Dot-Com Bubble to the 2015 Chinese Bubble is largely reflected in the decoupled nature of the dynamic correlations.

Our findings provide evidence that international contagion and exposure during these periods is fundamentally weak, but the significance of policy implications is highlighted. In particular, we show how the liberalization of the Chinese stock market had the unintended consequence of initiating a bubble. Overall, as policy has evolved in QFII and QDII, the effects of “process switching” and economic conditions within these countries must be highlighted. The Lucas Critique supports the theoretical basis that with a transition in economic policy, the qualitative nature of economic variables is also altered. Together our results suggest that the co-movement of the Chinese and U.S. markets during financially idiosyncratic periods, such as bubbles, are not originally derived from the spread of volatility clustering alone. For example, it may be inferred that the contagion between the two economies is partially fueled by irrational noise.

One limitation of our study is that we have two bubble periods for the U.S. and only one for the Chinese Economy. Relatedly, the U.S. stock market is much more mature than that of the Chinese markets. It will be important to revisit this investigation when the Chinese market is more mature.

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## Appendix A

### *Calibration of LPPL Model for Shanghai and Shenzhen Stock Indexes*

In the Shanghai stock index from 5 May 2014–15 September 2015 (Figure 1a), three consecutive peaks identified by implementing the price peaks algorithm (see [Pele 2012](#)) are:

$$i = 244 \text{ (6/4/2015)}, j = 254 \text{ (05/27/2015)}, \text{ and } k = 258 \text{ (6/2/2015)}$$

Using these peaks, the initial values of the parameters of the LPPL model are computed as follows:

$$\rho = \frac{j-i}{k-j} = \frac{254-244}{258-254} = 2.5$$

$$\text{Critical time, } t_c = \frac{\rho k - j}{\rho - 1} = 260.6667, \quad \omega = \frac{2\pi}{\ln(\rho)} = 6.857196$$

$$\text{and } \varnothing = \pi - \omega \ln(t_c - k) = -12.64769.$$

Initial values  $A = 8.41312$  and  $B = -0.0035037$  are computed by using the linear least-squares fit to an exponential function. The residual standard error is 0.06849.

Using the initial values, we fit the LPPL algorithm:

$$\ln p(t) = A + B(t_c - t)^m (1 + C \cos(\omega \ln(t_c - t) + \varnothing))$$

to the data.

The final values of the parameter are:

$t_c = 259$  (6/03/2015),  $A = 8.436199$ ,  $B = -0.005424$ ,  $m = 0.940693$ ,  $C = 0.125600$ ,  $\omega = 7.386984$ ,  $\varnothing = -2.106206$ , with residual standard error of 0.04042.

The final parameter values and the substantial reduction of the residual standard error indicate that a bubble was likely in progress (see [Liberatore 2010](#)). The actual Shanghai index peak was on 6 December 2015.

In the Shenzhen stock index from 5 May 2014–15 September 2015 (Figure 1b), three consecutive peaks identified by implementing the price peaks algorithm (see [Pele 2012](#)) are:

$$i = 245 \text{ (5/13/2015), } j = 254 \text{ (5/27/2015), and } k = 259 \text{ (6/3/2015).}$$

The initial parameter values are:

$t_c = 265.25$ ,  $A = 7.7651793$ ,  $B = -0.00408038$ ,  $m = 0.97478865$ ,  $C = 0.02102474$ ,  $\omega = 10.82082$ , and  $\varnothing = -16.423917$  with residual standard error of 0.09078.

$C \approx 0$  and there is not a significant reduction in the residual standard error. The actual Shenzhen index peak was on 12 June 2015.

## Notes

- <sup>1</sup> [Garber \(1990\)](#) is one of the earliest works that investigate bubbles.
- <sup>2</sup> [Scherbina and Schlusche \(2014\)](#) provide a nice survey on asset price bubbles.
- <sup>3</sup> Unreported Augmented Dickey-Fuller and Phillips-Perron tests of the sample returns strongly reject the null hypothesis of the presence of a unit root.
- <sup>4</sup> In a recent study, [Akhtaruzzaman et al. \(2021\)](#) investigate the spillover effects between firms in the U.S. and firms in China and report that both U.S. and Chinese firms transmit more volatility than they receive.

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