

Inferring Fundamental Value and Crash Nonlinearity from Bubble Calibration

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Abstract

Identifying unambiguously the presence of a bubble in an asset price remains an unsolved problem in standard econometric and financial economic approaches. A large part of the problem is that the fundamental value of an asset is, in general, not directly observable and it is poorly constrained to calculate. Further, it is not possible to distinguish between an exponentially growing fundamental price and an exponentially growing bubble price.

In this paper, we present a series of new models based on the Johansen-Ledoit-Sornette (JLS) model, which is a flexible tool to detect bubbles and predict changes of regime in financial markets. Our new models identify the fundamental value of an asset price and a crash nonlinearity from a bubble calibration. In addition to forecasting the time of the end of a bubble, the new models can also estimate the fundamental value and the crash nonlinearity, meaning that identifying the presence of a bubble is enabled by these models. Besides, the crash nonlinearity obtained in the new models presents a new approach to possibly identify the dynamics of a crash after a bubble.

We test the models using data from three historical bubbles ending in crashes from different markets. They are: the Hong Kong Hang Seng index 1997 crash, the S&P 500 index 1987 crash (black Monday) and the Shanghai Composite index 2009 crash. All results suggest that the new models perform very well in describing bubbles, forecasting their ending times and estimating fundamental value and the crash nonlinearity.

The performance of the new models is tested under both the Gaussian residual assumption and non-Gaussian residual assumption. Under the Gaussian residual assumption, nested hypotheses with the Wilks statistics are used and the p-values suggest that models with more parameters are necessary. Under non-Gaussian residual assumption, we use a bootstrap method to get type I and II errors of the hypotheses. All tests confirm that the generalized JLS models provide useful improvements over the standard JLS model.

Keywords: financial bubbles, crash, prediction, fundamental value, nonlinearity, Wilks statistics, bootstrap

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I. INTRODUCTION

Financial bubbles are generally defined as transient upward accelerations of price above a fundamental value [2, 10, 14]. Fundamental value reflects the intrinsic value (and is sometimes called this) of the asset itself. It is ordinarily calculated by summing the future incomes generated by the asset, which are discounted to the present. However, as the future income flow is uncertain and not known in advance, and since the interest rates that should be used to discount future cash flows are bound to change in ways not yet known at the time of the calculation, the fundamental value of the asset is usually hard to estimate. In this sense, identifying unambiguously the presence of a bubble remains an unsolved problem in standard econometric and financial economic approaches [4, 12].

The Johansen-Ledoit-Sornette (JLS) model [7–9] provides a flexible framework to detect bubbles and predict changes of regime in the price time series of a financial asset. It combines (i) the economic theory of rational expectation bubbles, (ii) behavioral finance on imitation and herding of investors and traders and (iii) the mathematical and statistical physics of bifurcations and phase transitions. The model considers the faster-than-exponential (power law with finite-time singularity) increase in asset prices decorated by accelerating oscillations as the main diagnostic of bubbles. It embodies a positive feedback loop of higher return anticipations competing with negative feedback spirals of crash expectations. Our group has made many successful predictions using JLS model, such as the 2006 - 2008 oil bubble [15], the Chinese index bubble in 2009 [6], real estate market in Las Vegas [20], South African stock market bubble [19] and US Repos market [18]. We also have recently developed new methods based on this model for forecasting rebounds of the stock market rather than crashes [17].

In this paper, we generalize the standard JLS model by inferring fundamental value of the stock and crash nonlinearity from bubble calibration. The new models can not only detect the crash time but also estimate the fundamental value and the crash nonlinearity. This means that our new model has the ability to identify the presence of a bubble, thereby addressing the problem stated at the beginning of this paper. With the estimated fundamental value, another famous unsolved problem becomes easier: distinguishing between an exponentially growing fundamental price and an exponentially growing bubble price. Furthermore, the new models can also detect the dynamics of crash after the bubble by

specifying how the price evolves towards the fundamental value during the crash.

We test the models using data from three historical bubbles from different markets that ended in significant crashes. They are: the Hong Kong Hang Seng index 1997 crash, the S&P 500 index 1987 crash (black Monday) and the Shanghai Composite index 2009 crash. All results suggest that the new models perform very well in describing bubbles, forecasting their ending times and estimating fundamental value and the crash nonlinearity.

The performance of the new models is tested under both the Gaussian residual assumption and non-Gaussian residual assumption. Under the Gaussian residual assumption, nested hypotheses with the Wilks statistics are used and the p-values suggest that models with more parameters are necessary. Under non-Gaussian residual assumption, we use a bootstrap method to get type I and II errors of the hypotheses. All tests confirm that the generalized JLS models provide useful improvements over the standard JLS model.

The paper is constructed as follows. In Section II, we introduce the standard JLS model and our new generalized JLS models. We then analyze three historical bubbles with the new models in Section III. In Section IV, we compare the generalized models statistically to confirm that these new models provide useful improvements over the standard JLS model. We conclude in Section V.

II. JLS MODELS

A. Standard JLS model

In the JLS model [7–9], the dynamics of a given asset is described as

$$\frac{dp}{p} = \mu(t)dt + \sigma(t)dW - \kappa dj, \quad (1)$$

where p is the asset price, μ is the drift (or trend) and dW is the increment of a standard Wiener process (with zero mean and unit variance). The term dj represents a discontinuous jump such that $j = 0$ before the crash and $j = 1$ after the crash occurs. The loss amplitude associated with the occurrence of a crash is determined by the parameter κ . Each successive crash corresponds to a jump of j by one unit. The dynamics of the jumps is governed by a crash hazard rate $h(t)$. Since $h(t)dt$ is the probability that the crash occurs between t and $t + dt$ conditional on the fact that it has not yet happened, we have $E_t[dj] = 1 \times h(t)dt +$

$0 \times (1 - h(t)dt)$ and therefore

$$E_t[dj] = h(t)dt. \quad (2)$$

Under the assumption of the JLS model, noise traders exhibit collective herding behaviors that may destabilize the market. The JLS model assumes that the aggregate effect of noise and fundamental traders can be accounted for by the following dynamics of the crash hazard rate

$$h(t) = B'(t_c - t)^{m-1} + C'(t_c - t)^{m-1} \cos(\omega \ln(t_c - t) - \phi'). \quad (3)$$

If the exponent $m < 1$, the crash hazard may diverge as t approaches a critical time t_c , corresponding to the end of the bubble. The second term in the r.h.s. of (3) takes into account the existence of a possible hierarchical cascade of panic acceleration punctuating the course of the bubble, resulting either from a preexisting hierarchy in noise trader sizes [21] and/or the interplay between market price impact inertia and nonlinear fundamental value investing [5].

The no-arbitrage condition reads $E_t[dp] = 0$, which leads to $\mu(t) = \kappa h(t)$. Taking the expectation of (1) with the condition that no crash has yet occurred gives $dp/p = \mu(t)dt = \kappa h(t)dt$. Using the crash hazard rate defined in (3) and integrating yields the so-called log-periodic power law (LPPL) equation for the price:

$$\ln p(t) = \mathcal{F}_{LPPL}(t), \quad (4)$$

where

$$\mathcal{F}_{LPPL}(t) = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln(t_c - t) - \phi), \quad (5)$$

$B = -\kappa B'/m$ and $C = -\kappa C'/\sqrt{m^2 + \omega^2}$. Note that this expression (4) with (5) describes the average price dynamics only up to the end of the bubble. The JLS model does not specify what happens beyond t_c . This critical t_c is the termination of the bubble regime and the transition time to another regime. For $0 < m < 1$, the crash hazard rate accelerates up to t_c but its integral up to t , which controls the total probability for a crash to occur up to t , remains finite and less than 1 for all times $t \leq t_c$. It is this property that makes rational for investors to remain invested knowing that a bubble is developing and that a crash is looming [7, 9]. Indeed, there is still a finite probability that no crash will occur during the lifetime of the bubble, including its end. The excess return $\mu(t) = \kappa h(t)$ is the remuneration that investors require to remain invested in the bubbly asset, which is exposed to a crash risk. The condition that the price remains finite at all time, including t_c , requires that $m \geq 0$.

Within the JLS framework, a bubble is identified when the crash hazard rate accelerates. According to (3), such accelerations occur when $m < 1$ and $B' > 0$, hence $B < 0$ since $m \geq 0$ by the condition that the price remains finite. We thus have a first condition for a bubble to occur:

$$0 < m < 1 . \quad (6)$$

This condition is the mathematical embodiment of our definition of a financial bubble, characterized by a faster-than-exponential growth as time approaches the critical time t_c . Indeed, it is straightforward to verify that the first-order and higher-order derivatives of the log-price diverge at t_c , in contrast with their finiteness for the standard exponential price model.

By definition, the crash rate should be non-negative. This imposes [16]

$$b \equiv -Bm - |C|\sqrt{m^2 + \omega^2} \geq 0 . \quad (7)$$

B. Modified JLS models

In an effort to study the fundamental price, we modify and generalize the JLS model as follows. We now write the price dynamics of an asset as

$$dp = \mu(t)pdt + \sigma(t)p dW - \kappa(p - p_1)^\gamma dj, \quad (8)$$

where the first two items of the right hand side define the standard geometrical Brownian motion and the third term is the jump.

When the crash occurs at some time t^* (implying $\int_{t^{*-}}^{t^{*+}} dj = 1$), the price drops abruptly by an amplitude $\kappa(p(t^*) - p_1)^\gamma$.

The motivations and the interpretation of the three parameters p_1 , κ and γ are as follows.

- For $\kappa = \gamma = 1$, the price drops from $p(t^{*-})$ to $p(t^{*+}) = p_1$, i.e., the price changes from its value just before the crash to a fixed well-defined valuation p_1 . In the spirit of Fama's analysis of the 19 October 1987 crash [1], if one interprets the asset price after the crash as the "right" price, i.e., the price discovery towards rational equilibrium without mispricing, the crash is nothing but an efficient assessment by investors of the "true" or fundamental value, once the panic has ended. Hence, p_1 can be interpreted as the fundamental price which is discovered during the crash dynamics.

- Then, κ can be thought of as a measure of market efficiency, that is, $1 - \kappa$ is the relative inaccuracy of the discovery of the fundamental price by the market. If, say, $\kappa = 0.5$, this means that the price has dropped by only half of its bubble component, and remains over-valued compared with its fundamental component.
- When different from 1, the exponent γ can be interpreted as embodying a nonlinear (i) over-reaction for small variations and under-reaction for large deviations ($0 < \gamma < 1$) or (ii) under-reaction for small variations and over-reaction for large deviations ($\gamma > 1$) from the fundamental value.

Since p_1 is a fixed parameter, the generalized JLS model implies that we should measure the price dynamics in the frame moving with the fundamental price. In other words, p_1 is the fundamental price at the beginning t_1 of the time period over which the bubble develops. In order to compare in a consistent way the realized price to this fixed parameter, it is necessary to discount the asset price continuously by the rate of return of the fundamental price. If $p_{\text{obs}}(t)$ denotes the empirical price observed at time t , this means that the price $p(t)$ that enters in expression (8) is defined by

$$p(t) = p_{\text{obs}}(t) \prod_{s=t_1+1}^t \frac{1}{(1 + r_f(s))^{\frac{1}{365}}} , \quad (9)$$

where $r_f(s)$ is the annualized growth (risk free) rate of the fundamental price. In our empirical analysis, we will take for $r_f(s)$ the annualized US 3-month treasury bill rate.

Applying again the no-arbitrage condition $E_t[dp] = 0$ to expression (8) leads to

$$\mu(t)p = \kappa(p - p_1)^\gamma h(t) . \quad (10)$$

Conditional on the absence of a crash, the dynamics of the expected price obeys the equation

$$dp = \mu(t)pdt = \kappa(p - p_1)^\gamma h(t)dt , \quad (11)$$

and the fundamental price must obey the condition $p_1 < \min p(t)$. For $\gamma = 1$, the solution of equation (11) generalizes (4) into

$$\ln[p(t) - p_1] = \mathcal{F}_{LPPL}(t) , \quad (12)$$

where $\mathcal{F}_{LPPL}(t)$ is again given by expression (5). For $\gamma \in (0, 1)$, the solution is

$$(p - p_1)^{1-\gamma} = \mathcal{F}_{LPPL}(t) , \quad (13)$$

where again $\mathcal{F}_{LPPL}(t)$ is given by expression (5). We do not consider the case $\gamma > 1$ which would give an economically non-sensible behavior, namely the price diverges in finite time before the crash hazard rate itself diverges.

In summary, we shall consider four models M_0 , M_1 , M_2 and M_3 , where some are nested in others. The goal will be to then apply statistical tests to the models to determine which are sufficient or not and which are necessary or not. In the following models, $\mathcal{F}_{LPPL}(t)$ below is given by expression (5).

0. Original JLS model M_0 : $p_1 = 0, \gamma = 1$ (with $\kappa < 1$):

$$p_{M_0}(t) = \exp(\mathcal{F}_{LPPL}(t)) . \quad (14)$$

1. M_1 : $p_1 \neq 0, \gamma = 1$:

$$p_{M_1}(t) = p_1 + \exp(\mathcal{F}_{LPPL}(t)) . \quad (15)$$

M_1 includes M_0 as a special case. In other words, M_0 is nested in M_1 .

2. M_2 : $p_1 = 0, \gamma \in (0, 1]$:

$$p_{M_2}(t) = \begin{cases} (\mathcal{F}_{LPPL}(t))^{\frac{1}{1-\gamma}}, & \gamma \in (0, 1) , \\ \exp(\mathcal{F}_{LPPL}(t)), & \gamma = 1 . \end{cases} \quad (16)$$

Since M_2 includes M_0 as a special case, M_0 is also nested in M_2 .

3. M_3 : $p_1 \neq 0, \gamma \in (0, 1]$:

$$p_{M_3}(t) = \begin{cases} p_1 + (\mathcal{F}_{LPPL}(t))^{\frac{1}{1-\gamma}}, & \gamma \in (0, 1) , \\ p_1 + \exp(\mathcal{F}_{LPPL}(t)), & \gamma = 1 . \end{cases} \quad (17)$$

M_3 includes all previous models, M_0 , M_1 and M_2 as special cases, so that M_0 , M_1 and M_2 are all nested in M_3 .

III. CALIBRATION AND RESULTS ON THREE HISTORICAL BUBBLES

A. Calibration method of the models

Given an observed asset time series of prices $\{p_{\text{obs}}(t)\}$, we first transform it into a price time series of discounted prices $\{p(t)\}$ by using expression (9). We next determine the three

parameters A , B and C in expression (5) for each model as a function of the other parameters, by solving analytically the system of three linear equations obtained by minimizing the square of deviations:

- $\ln[p(t)] - \mathcal{F}_{LPPL}(t)$ for M_0 ,
- $\ln[p(t) - p_1] - \mathcal{F}_{LPPL}(t)$ for M_1 ,
- $[p(t)]^{1-\gamma} - \mathcal{F}_{LPPL}(t)$ for M_2 and
- $[p(t) - p_1]^{1-\gamma} - \mathcal{F}_{LPPL}(t)$ for M_3 .

We then determine the other parameters for each model using a Taboo search (to find initial parameter estimates) coupled with a Levenberg-Macquardt algorithm. We constrain the values of plausible parameters as follows:

1. the fundamental price p_1 should be larger than $0.2p_{\min}$, where $p_{\min} := \text{Min}[p(t)]$ over the fitting time interval.
2. The fit parameters t_c , m , p_1 and γ should not be on the boundary of the search intervals. They should deviate from these boundaries by at least 1% in relative amplitude.
3. Among all the fits satisfying the above two conditions, the one with the smallest sum of normalized residuals is selected. The cost function we use here is the sum of squares of the relative discounted price differences

$$R(t) = \frac{p(t) - p_M(t)}{p_M(t)}, \quad (18)$$

where $p_M(t)$ stands for one of the expressions (14-17).

The critical time t_c corresponding to the end of the bubble is searched in $[t_2; t_2 + 0.4(t_2 - t_1)]$, where the time window of analysis is $[t_1; t_2]$. The exponent m is constrained in $[10^{-5}; 1 - 10^{-5}]$. The log-angular frequency ω is searched in $[0.01; 40]$. The phase ϕ can take values in $[0, 2\pi - 10^{-5}]$. The fundamental price p_1 is in $[0.01; 0.99p_{\min}]$ and then restricted by condition (i) above.

B. Results

We calibrate models $M_0 - M_3$ to three well-documented bubbles, which ended in large crashes:

- Hong Kong Hang Seng index (HSI) ($t_1 = \text{Feb. 1, 1995}$, $t_2 = \text{March 13, 1997}$),
- S&P 500 index (GSPC) ($t_1 = \text{Sept. 1, 1986}$, $t_2 = \text{Aug. 26, 1987}$),
- Shanghai Composite index (SSEC) ($t_1 = \text{Oct. 24, 2008}$, $t_2 = \text{July 10, 2009}$).

1. Presentation and discussion

The results are shown in Figs. 1 - 3 and the corresponding parameters are given in Tables I - III. Visually, all models seem to perform similarly, with the determined critical times t_c close to the true time of the crash. We note that the parameters p_1 and γ in M_1, M_2 and M_3 depart significantly from their reference values $p_1 = 0$ and $\gamma = 1$ characterizing model M_0 .

Model M'_0 corresponds to model M_0 with a slightly different cost-function. Instead of minimizing the sum of the squares of terms given by (18), for t going from t_1 to t_2 , the parameters of M'_0 are those of model M_0 obtained by minimizing the sum of the squares of the difference $\ln[p_{M_0}(t)] - \mathcal{F}_{LPP}(t)$. Since $\ln y - \ln x = (y - x)/x + \mathcal{O}[(y - x)/x]^2$, the two methods should give similar results and the results summarized in tables I-III confirm this expectation.

Results of detailed statistical comparisons between the four models are shown below. Tables I-III suggest that the five models perform almost equivalently in their ability to fit the price accelerations and to determine the time t_c of the peak of the bubbles. One can note a remarkable stability and consistency of the estimators for the two crucial parameters, the exponent m and the angular log-frequency ω . However, models M_1 and M_3 provide an interesting estimation of the size of the bubble, which appears stable with respect to these two specifications: at the beginning of the calibration interval, for the Hong Kong bubble, models M_1 and M_3 estimate that the bubble component might have been already accounting for 71% to 80% of the observed price. At the end of the bubble, the bubble component is between 85% to 90% of the observed price. Similar values are found for the two other case

studies. An exception is for the Shanghai Composite index bubble, for which model M_3 suggests that the fundamental price was 92% of the observed price at the beginning of the calibrating interval and about half of the observed price at its peak.

The models provide a method to measure the amplitude of the crash that follows the bubble peak. Consider two types of drawdown after the peak: (i) $DD_{[2\text{months}]}$ is the two-months drop measured from the peak; (ii) DD_{\max} is the peak-to-valley drawdown from the peak to the minimum of the asset price after the crash. We calculate the magnitude of the crash compared to the over-valued prices as follows. The ratio between the crash magnitude and over-valued prices is estimated as:

$$RC_i = \frac{DD_i}{p_{\text{obs}}(t_p) - p_1 \prod_{s=t_1+1}^t (1 + r_f(s))^{\frac{1}{365}}} \quad i \in \{[2\text{months}], \max\}. \quad (19)$$

During the crashes, the hazard rate in Eq. 11) should be 1. Then comparing the definition of RC and Eq. (11), one can easily find that $\kappa = RC$ for the models whose $\gamma = 1$ (M_0, M_1, M'_0). For the other models, κ is different from RC . These values are reported in tables I-III.

2. Consistency test of the calibrations

According to the specification of [11], we should verify that the calibrations discussed above are self-consistent, i.e., the residuals are stationary. This verification step was proposed by [11] as a possible solution to the problems identified by [3] and [13] resulting from the calibration of non-stationary prices.

In order to check that the normalized residuals are stationary for all the four models, we use the Phillips-Perron and the Dickey-Fuller unit root tests. The null hypothesis H_0 is that the normalized residuals are not stationary, i.e. they have a unit root. In order to have reasonable statistics, we consider time windows of fixed length of 175, 250 or 550 trading days. We identify these windows in time series much larger than the (t_1, t_2) intervals used to identify the bubbles (given at the top of Sec. III B). The interval lengths correspond to the different values of $t_2 - t_1$ for the respective case studies. We choose overlapping intervals with the start of neighboring intervals separated by 25 days. There are 303 windows of size 550 trading days for the HSI from Jan. 1, 1987 to Feb. 25, 2010; 800 windows for the GSPC index from Feb. 2, 1954 to Feb. 10, 2010 with size of 250 trading days; 167 windows of SSEC from Aug. 3, 1997 to Jan. 22, 2010 of size of 175 trading days. Note that we choose these

dates as the window boundaries because: (i) the chosen (t_1, t_2) intervals identified at the top of Sec. IIIB should be one of the windows we get here; (ii) up to the data collection date (Feb. 26, 2010), we want to get as many windows as we can. Using the statistical confidence level of 99%, we determine the fraction of those windows which reject the Phillips-Perron and the Dickey-Fuller unit root tests (H_1), i.e., which qualify as stationary. The results are presented in table IV. We conclude that most of the residuals are found stationary, which support the validity of our calibration procedure.

Previous works have identified the domain of parameters of the calibration of the JLS model M_0 which is the most relevant (Johansen and Sornette, 2006; Jiang et al., 2010). These conditions, referred to as the LPPL (log-period power law) conditions, are

$$B > 0; \quad 0.1 \leq m \leq 0.9; \quad 6 \leq \omega \leq 13; \quad -1 \leq C \leq 1. \quad (20)$$

Imposing that the calibrations obey these LPPL conditions (20), we find in Table V that the fraction of the above windows analyzed in Table IV which fulfill the stationary conditions is significantly increased, augmenting our trust of the quality of the calibration and of the relevance of this class of models.

IV. STATISTICAL COMPARISONS OF THE FOUR GENERALIZED JLS MODELS

A. Standard Wilks test of nested hypotheses assuming independent and normally distributed residuals

Let us consider the five pairs of models with nested structure: $(M_0 \subset M_1)$, $(M_0 \subset M_2)$, $(M_1 \subset M_3)$, $(M_2 \subset M_3)$, and $(M_0 \subset M_3)$. Let us denote M_l as the model with the smaller number of parameters and M_h that with the larger number of parameters. For each pair, we use Wilks test of nested hypotheses in terms of the log-likelihood ratios to decide between the two hypotheses:

H_0 : M_l is sufficient and M_h is not necessary.

H_1 : M_l is not sufficient and M_h is needed.

We first present in this subsection the tests assuming that the residuals of the calibration of the models to the asset price time series are normally and independently distributed. In the next subsection, we loosen this restriction.

For each model M_i , $i = 0, 1, 2, 3$, let us denote the normalized residuals defined by expression (18) by $R_i(t)$ and assume that they are i.i.d. Gaussian. For sufficiently large time windows, and noting N the number of trading days in the fitted time window $[t_1; t_2]$, the Wilks log-likelihood ratio reads

$$T = 2 \log \frac{L_{h,max}}{L_{l,max}} = 2N \ln \frac{\sigma_l}{\sigma_h} + \frac{\sum_{t=1}^N R_l^2(t)}{\sigma_l^2} - \frac{\sum_{t=1}^N R_h^2(t)}{\sigma_h^2}, \quad (21)$$

where R_l and σ_l (respectively R_h and σ_h) are the residuals and their corresponding standard deviation for M_l (respectively M_h).

In the large N limit, and under the above conditions of asymptotic independence and normality, the T -statistics is distributed with a χ_k^2 distribution with k degrees of freedom, where k is the difference between the number of parameters in M_h and M_l . We have $k = 1$ for the pairs (M_0, M_1) , (M_0, M_2) , (M_1, M_3) , (M_2, M_3) , and $k = 2$ for (M_0, M_3) . The p -values associated with the T -statistics given by (21) for each of the five pairs are reported in Table VI. The summary of that table is:

- Hong Kong Hang Seng index (HSI) from Feb. 1, 1995 to March 13, 1997: Model M_0 is never rejected and the standard JLS model is sufficient.
- S&P 500 index (GSPC) from Sept. 1, 1986 to Aug. 26, 1987: Model M_0 is rejected with strong statistical confidence in favor of M_1 , M_2 and M_3 . However, when comparing M_1 and M_2 to M_3 , we find that M_3 is not necessary. Therefore, we conclude that the structure of the S&P 500 index bubble requires the introduction of either a fundamental price p_1 or of a nonlinear crash amplitude as a function of mispricing (price for M_0 and M_2), but that both ingredients together are not necessary.
- Shanghai Composite index (SSEC) from Oct. 24, 2008 to July 10, 2009: Only M_3 improves on M_0 at a confidence level of 92.3% that can be considered as acceptable, while M_1 and M_2 are not significantly better than M_0 for standard confidence levels. Consistent with M_3 being rather significantly better than M_0 , it is also better than M_1 and M_2 , which are themselves not significantly improving on M_0 . There seems to

exist both a fundamental value component and a nonlinear over-reaction to mispricing in the unfolding of this Chinese bubble.

B. Comparison between models by bootstrapping to account for non-normality and dependence between residuals

Consider a pair of models ($M_l \subset M_h$). Let us assume that M_l is the correct generating model of the data. The calibration of M_l to the data gives a specific set of parameters as well as a specific realization of residuals. We then use this specification of the model M_l and its residuals to generate 1000 synthetic time series. A given synthetic time series is the calibrated M_l time series on which we add residuals obtained by randomly reshuffling the previously obtained residuals. Thus, the 1000 synthetic time series differ from each other only by the reshuffling of the residuals. We then calibrate the two models M_l and M_h on each of these 1000 synthetic time series and calculate the difference of the sum of the square of residuals of the fits of these two models. We thus have a list of 1000 different d_n , $n = 1, \dots, 1000$. Comparing with the corresponding difference d_{fit} (between M_l and M_h) gives us a realistic estimation of the p -value for the null hypothesis that M_l is the correct generating model of the data. Specifically, the p -value is the fraction among the 1000 d_n 's that are *larger* than d_{fit} . For instance, if all values d_n are smaller than d_{fit} , we obtain $p = 0$, i.e., it is very improbable that the difference in quality of fit between M_l and M_h results solely from the structure of the models and of the residues. We can reject the null and conclude that M_h is a better necessary model.

The second test we perform starts with the hypothesis that the true generating process is M_h . Thus, the 1000 synthetic time series are now generated by using model M_h calibrated on the data and its residuals. Then, the p -value for this null is determined as the fraction among the 1000 d_n 's that are *smaller* than d_{fit} .

Table VII summarizes the results, which improve on those shown in Table VI by relaxing the conditions of normality and of independence between the daily residuals of the calibration. The bootstraps are performed by reshuffling the residuals of the fit “every day” or in blocks of 25 continuous days (“every 25 days”), which is in blocks of 25 continuous days. The later allows us to keep the dependence structure over 25 days to test its possible impact on the p -values. Reshuffling every day destroys any dependence in the residuals, while keeping

their one-point (possibly non-Gaussian) statistics.

For HSI, taking into account the dependence structure of the residuals up to 25 days confirm the results already found in Table VI that the standard JLS model M_0 is sufficient to explain the observed financial bubble. For GSPC, the results also confirm those of the Wilks test in Table VI, that M_1 and M_2 improve significantly on M_0 , while M_3 is not necessary. For SSEC, also in agreement with Table VI, model M_3 is found to be the best and to be significant at the 95% confidence level.

Overall, these tests confirm that the generalized JLS models seem to provide useful improvements over the standard JLS model, both in terms of their explanatory power and in the extraction of additional information, specifically the fundamental price p_1 and a possible nonlinear dependence of the crash amplitude as a function of mispricing.

V. CONCLUSION

In this paper, we generalized the JLS model by inferring the fundamental value and crash nonlinearity from bubble calibration. In the generalized model, one can not only predict the crash time of a stock, but also estimate the fundamental value of that stock. Besides, the crash nonlinearity can also be estimated.

Three historical bubbles from different markets are tested by the generalized models. All the results suggest that the new models perform very well in describing bubbles, predicting crash time and estimating fundamental value and the crash nonlinearity.

The performance of the new models is tested both under the Gaussian and non-Gaussian residual assumptions. Under the Gaussian residual assumption, nested hypothesis testing with the Wilks statistics is used and the p-values suggest models with more parameters are necessary. Under non-Gaussian residual assumption, we use bootstrap method and get the type I and II errors of the hypothesis. All those tests confirm that the generalized JLS models provide useful improvements over the standard JLS model.

HSI	t_c	$ t_c - t_p $	m	ω	ϕ	$\frac{p_f(t_1)}{p(t_1)}$	$\frac{p_f(t_p)}{p(t_p)}$	γ	$RC_{[2\text{months}]}$	RC_{\max}	RMS
M_0	27-Jul-1997	10	0.19	6.97	0.00	-	-	-	0.46	0.62	0.0320
M_1	11-Jul-1997	26	0.25	6.63	0.78	0.20	0.10	-	0.52	0.69	0.0320
M_2	12-Jul-1997	25	0.03	6.64	0.87	-	-	0.13	0.46	0.62	0.0319
M_3	12-Jul-1997	25	0.03	6.65	4.04	0.29	0.15	0.11	0.54	0.73	0.0319
M'_0	09-Jul-1997	28	0.39	6.53	3.30	-	-	-	0.41	0.55	0.0323

TABLE I: Results of the calibration of models $M_0 - M_3$ for the Hong Kong Hang Seng index (HSI) from Feb. 1, 1995 to March 13, 1997. t_c is the critical time of a given model corresponding to the end of the bubble and the time at which the crash is the most probable. t_1 is the beginning of the fitting interval. t_p is the time when the asset value peaks before the crash. The relative amplitude of the crash following the peak of the bubble is given by $RC_{[2\text{months}]}$ and RC_{\max} , which are calculated using expression (19) from the following drawdown amplitudes: (i) $DD_{[2\text{months}]}$ is the two-months drop measured from the peak; (ii) DD_{\max} is the peak-to-valley drawdown from the peak to the minimum of the asset price. RMS is the root mean square of the distances between historical prices and the model values, i.e., the square root of the sum of the squares of terms given by (18), for t going from t_1 to t_2 , where t_2 is the last date of the time window used for the analyses. The model denoted M'_0 corresponds to model M_0 with a different calibration method, as explained in the text.

GSPC	t_c	$ t_c - t_p $	m	ω	ϕ	$\frac{p_f(t_1)}{p(t_1)}$	$\frac{p_f(t_p)}{p(t_p)}$	γ	$RC_{[2\text{months}]}$	RC_{\max}	RMS
M_0	13-Sep-1987	19	0.70	6.62	0.00	-	-	-	0.34	0.35	0.0196
M_1	03-Sep-1987	9	0.68	6.10	0.00	0.18	0.14	-	0.40	0.40	0.0190
M_2	05-Sep-1987	11	0.63	6.09	0.00	-	-	0.72	0.34	0.35	0.0191
M_3	03-Sep-1987	9	0.64	6.10	0.00	0.18	0.14	0.64	0.40	0.40	0.0190
M'_0	26-Aug-1987	1	0.68	5.59	0.14	-	-	-	0.32	0.33	0.0187

TABLE II: Same as Table I for the S&P 500 index (GSPC) from Sept. 1, 1986 to Aug. 26, 1987.

SSEC	t_c	$ t_c - t_p $	m	ω	ϕ	$\frac{p_f(t_1)}{p(t_1)}$	$\frac{p_f(t_p)}{p(t_p)}$	γ	$RC_{[2\text{months}]}$	RC_{\max}	RMS
M_0	29-Jul-2009	2	0.63	16.60	0.00	-	-	-	0.23	0.23	0.0258
M_1	24-Jul-2009	3	0.77	15.86	1.94	0.36	0.19	-	0.29	0.29	0.0256
M_2	21-Jul-2009	6	0.69	15.52	6.28	-	-	0.99	0.23	0.23	0.0257
M_3	24-Jul-2009	3	0.65	15.96	2.49	0.92	0.49	0.20	0.45	0.45	0.0254
M'_0	24-Jul-2009	3	0.68	15.86	5.12	-	-	-	0.23	0.23	0.0256

TABLE III: Same as Table I for the Shanghai Composite index (SSEC) from Oct. 24, 2008 to July 10, 2009.

Percentage of stationary	M_0	M_1	M_2	M_3
303 HSI windows from Jan. 1, 1987 to Feb. 25, 2010, length 550.				
Phillips-Perron	96.7%	98.0%	96.7%	97.7%
Dickey-Fuller	96.7%	98.0%	96.7%	97.7%
800 GSPC windows from Feb. 2, 1954 to Feb. 10, 2010, length 250.				
Phillips-Perron	90.6%	91.0%	91.8%	91.8%
Dickey-Fuller	90.6%	91.0%	91.8%	91.8%
167 SSEC windows from Aug. 3, 1997 to Jan. 22, 2010, length 175.				
Phillips-Perron	96.4%	97.0%	96.4%	97.0%
Dickey-Fuller	96.4%	97.0%	96.4%	97.0%

TABLE IV: Percentage of stationary residuals for the Phillips-Perron and Dickey-Fuller tests. Significance level: 99%.

Percentage of stationary under LPPL constrains	M_0	M_1	M_2	M_3
303 HSI windows from Jan. 1, 1987 to Feb. 25, 2010, length 550.				
P_{LPPL}	0.99%	0.99%	2.64%	1.98%
Phillips-Perron	100%	100%	100%	100%
Dickey-Fuller	100%	100%	100%	100%
800 GSPC windows from Feb. 2, 1954 to Feb. 10, 2010, length 250.				
P_{LPPL}	4.50%	6.00%	4.50%	5.87%
Phillips-Perron	95.7%	100%	97.9%	100%
Dickey-Fuller	95.7%	100%	97.9%	100%
167 SSEC windows from Aug. 3, 1997 to Jan. 22, 2010, length 175.				
P_{LPPL}	4.19%	4.79%	8.38%	9.58%
Phillips-Perron	93.8%	92.9%	100%	100%
Dickey-Fuller	93.8%	92.9%	100%	100%

TABLE V: Percentage of stationary residuals, as qualified by the Phillips-Perron and Dickey-Fuller tests, which obey the LPPL conditions (20). The variable P_{LPPL} gives the fraction of fits that satisfy the conditions (20), independently of whether their residuals are stationary or not. Significance level: 99%.

	(M_0, M_1)	(M_0, M_2)	(M_1, M_3)	(M_2, M_3)	(M_0, M_3)
HSI	0.4710	0.2210	0.3221	0.9626	0.4723
GSPC	0.0003	0.0006	0.7930	0.2150	0.0012
SSEC	0.1405	0.2494	0.0863	0.0516	0.0775

TABLE VI: p -value of the null hypothesis H_0 for pairs of models (M_l, M_h) that M_l is sufficient and M_h is not necessary, using Wilks log-likelihood ratio statistics. Low p -value indicates the improvement of M_h compared to M_l is significant and H_0 is rejected.

	(M_0, M_1)	(M_0, M_2)	(M_0, M_3)	(M_1, M_3)	(M_2, M_3)
HSI shuffle every day					
M_l true	0	0	0	0.05	0.75
M_h true	0	0	0	0.10	0.60
HSI shuffle every 25 days					
M_l true	0.46	0.20	0.42	0.26	0.76
M_h true	0.42	0.12	0.38	0.18	0.70
GSPC shuffle every day					
M_l true	0	0	0	0.35	0.45
M_h true	0.05	0	0	0.45	0.40
GSPC shuffle every 25 days					
M_l true	0.05	0	0.05	0.40	0.50
M_h true	0	0	0	0.50	0.45
SSEC shuffle every day					
M_l true	0	0	0	0.05	0.35
M_h true	0	0.05	0	0.05	0.50
SSEC shuffle every 25 days					
M_l true	0.14	0.08	0.04	0.04	0.38
M_h true	0.12	0.06	0.06	0.08	0.40

TABLE VII: p -values calculated by bootstrapping (see text for explanation). Low p -value indicates the improvement of M_h compared to M_l is significant.

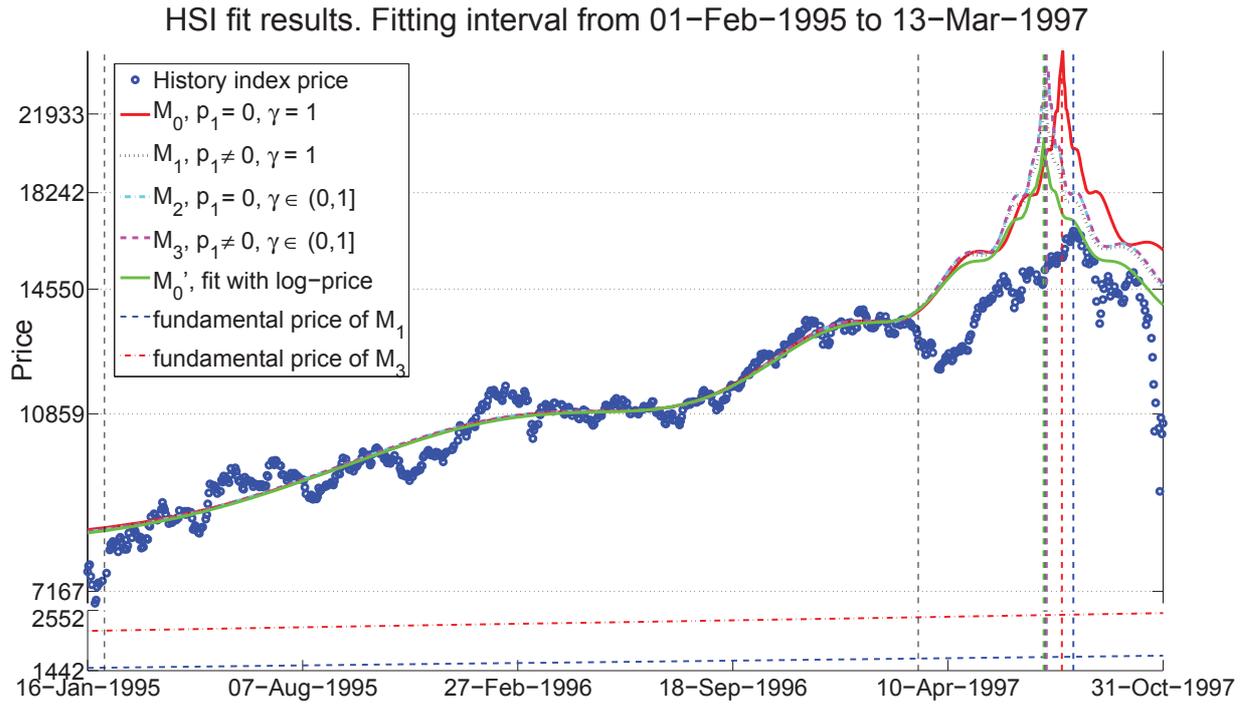


FIG. 1: Calibration of the different models to the Hong Kong Hang Seng Index. The fit interval is shown with vertical black dashed lines. The fitted critical time t_c when the crash is most probable according the modified JLS models are marked by vertical dashed lines with the same color as the corresponding fits with each model. The historical close prices are shown as blue empty circles. The fundamental price for M_1 and M_3 are also shown as the almost horizontal dashed lines (beware of the break in the vertical scales for low values).

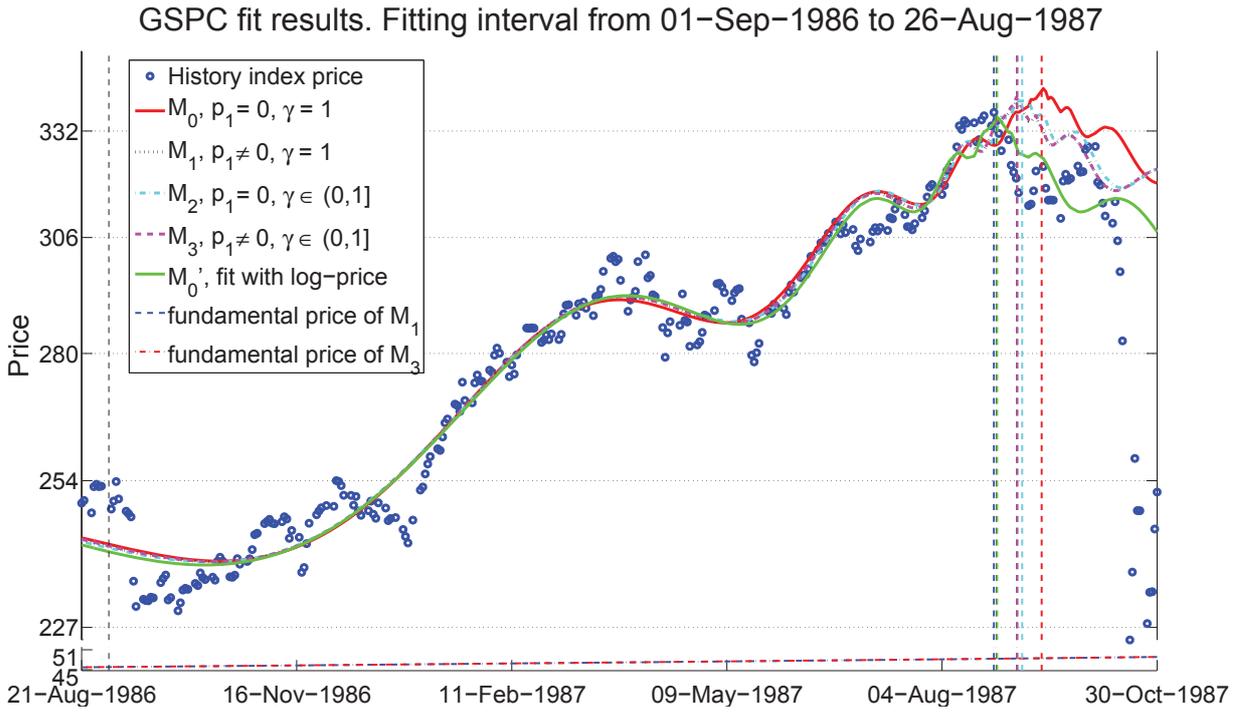


FIG. 2: Same as figure 1 for the S & P 500 Index.

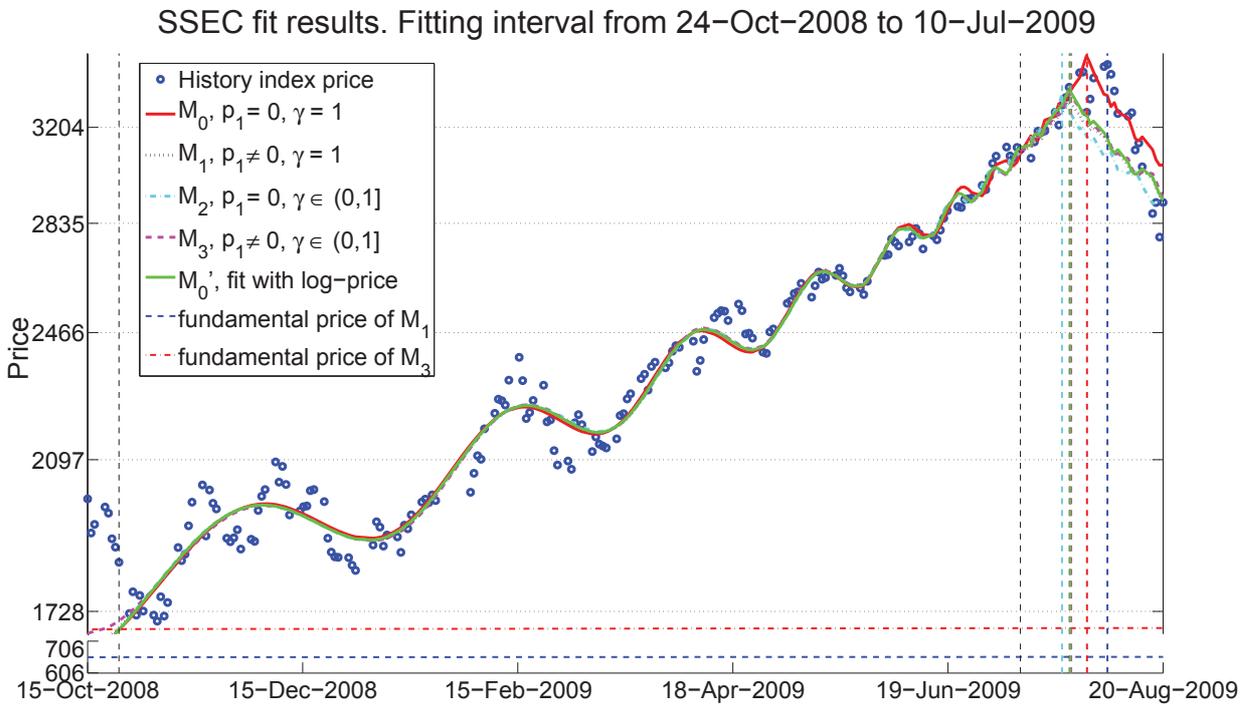


FIG. 3: Same as figure 1 for the Shanghai Composite Index.

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