

Growth enterprise market in Hong Kong

Efficiency evolution and long memory in return and volatility

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Received 25 January 2019
Revised 7 May 2019
Accepted 2 July 2019

Abstract

Purpose – Growth enterprise market (GEM) in Hong Kong is acknowledged as one of the world's most successful examples of small and medium enterprise (SME) stock market. The purpose of this paper is to examine the evolving efficiency and dual long memory in the GEM. This paper also explores the joint impacts of thin trading, structural breaks and inflation on the dual long memory.

Design/methodology/approach – State-space GARCH-M model, Kalman filter estimation, factor-adjustment techniques and fractionally integrated models: ARFIMA–FIGARCH, ARFIMA–FIAPARCH and ARFIMA–HYGARCH are adopted for the empirical analysis.

Findings – The results indicate that the GEM is still weak-form inefficient but shows a tendency towards efficiency over time except during the global financial crisis. There also exists a stationary long-memory property in the market return and volatility; however, these long-memory properties weaken in magnitude and/or statistical significance when the joint impacts of the three aforementioned factors were taken into account.

Research limitations/implications – A forecasts of the hedging model that capture dual long memory could provide investors further insights into risk management of investments in the GEM.

Practical implications – The findings of this study are relevant to market authorities in improving the GEM market efficiency and investors in modelling hedging strategies for the GEM.

Originality/value – This study is the first to investigate the evolving efficiency and dual long memory in an SME stock market, and the joint impacts of thin trading, structural breaks and inflation on the dual long memory.

Keywords Inflation, Structural breaks, Thin trading, Dual long memory, Evolution towards efficiency

Paper type Research paper

1. Introduction

As a Special Administrative Region of the People's Republic of China with high degree of autonomy in political and economic systems, Hong Kong is renowned for its extent of trade openness and dynamic economic structure. Over the last seven decades, the economic success of Hong Kong is undisputable due to the fact that its economy has been experiencing structural transformation from a regional hub for industrial manufacturing to a major international financial centre. This successful transformation is largely attributable to the liberal economic policies, effective corporate governance, and free and transparent flow of information.

Being a trade gateway to Mainland China and having strong business relations with many other Asian economies, Hong Kong is strategically situated in a high growth region and has now become one of the world's most unfettered economies. According to WTO (2018) and UNCTAD (2018), Hong Kong is the world's seventh largest exporter of merchandise trade and



the world's second largest investor and host. This service-oriented economy is also remarked as the fourth greatest foreign exchange market in the world and the biggest offshore RMB (Renminbi, the Chinese currency) clearing centre (BIS, 2018). Furthermore, Hong Kong has remarkably weathered several critical shocks since the 2000s such as global financial crisis (GFC), stock market crashes, Chinese market turmoil, typhoons, chaos and the transfer of sovereignty from London to Beijing (Scobell and Gong, 2017).

For decades, Hong Kong has striven to become the third leading global financial centre, and Hong Kong Stock Exchange (HKEX) has developed into the world's sixth largest stock market and the third in Asia, providing opportunities for several multinational companies and conglomerates to raise capital. In 1999, HKEX introduced the growth enterprise market (GEM) as a second board, also known as an alternative market to the main market, to offer a fund-raising mechanism and a credible identity for small and medium enterprises (SMEs), who are ineligible to be listed on the main board. The GEM's operation is grounded on the two principles of "buyer beware" and "let the market decide", along with a comprehensive disclosure regime. The GEM follows rules and regulations designed to foster a practice of self-compliance by the listed enterprises, sponsors and market makers in the discharge of their responsibilities.

Compared to the Main Board of HKEX, the GEM adheres to less stringent rules and regulations, lower requirements for listing and information disclosure, and holds a narrower investor base and higher investment risk. The GEM is operating under the sponsor-driven model which involves the participation of sponsor and market maker. The sponsor is a qualified advising agent approved by HKEX to ensure the quality of listing applicants. The market maker or liquidity provider, who is a member of HKEX, trades the listed securities to boost the market liquidity. Furthermore, another important characteristic of the GEM is that it exhibits a higher under-pricing level of initial public offerings (IPOs) than that of the Main Board. Vong and Zhao (2008) showed that such a high level of IPO under pricing (approximately 20 per cent) in the GEM is attributable to the *ex post* volatility of after-market returns, the timing effects and the geographic locations (i.e. H shares[1]). On the other hand, the under pricing of IPOs in ChiNext, which is a SME stock market in China, is driven by offline oversubscription, issue size, market momentum (Deng and Zhou, 2015), the ongoing litigation risk and the trademark infringement risk (Hussein *et al.*, 2019).

Hong Kong Special Administrative Region Government has long-recognised SMEs as the true economic powerhouse of Hong Kong's economy. Nevertheless, their growth is obstructed by a credit gap of US\$10.2bn (IFC, 2013) due to lack of transparency, low credit rating and high financial risk associated with small businesses. In the SME financing landscape, the GEM emerges as an effective mechanism for SMEs to raise long-term capital. In fact, since its establishment in 1999–2016, the GEM has successfully raised around US\$22.7bn for SMEs through IPOs and secondary public offerings. In 2015, the funds raised through this market peaked at US\$2.8bn, which is equivalent to a significant 27.9 per cent of the SME credit gap in Hong Kong. Therefore, the GEM is considered one of the world's most successful examples of SME stock markets (Peterhoff *et al.*, 2014), making it attractive for researchers.

Even though the GEM plays an important role in closing the SME credit gaps in Hong Kong, it has received limited attention. Specifically, market efficiency in this alternative markets and their important roles in fostering economic growth have largely been neglected in the literature. Since the GEM is at an early stage of development, it is hardly conceivable for it to be efficient since it takes time for the price discovery process to fully incorporate new information. However, as market participants become more sophisticated, and the regulatory environment and trading system become better developed over time, the degree of efficiency in such an SME market will gradually improve. Therefore, it is necessary to analyse the evolution of weak-form efficiency rather than just addressing the matter of whether or not the market is efficient in the weak form. An analysis of efficiency evolution can reveal a potential tendency towards efficiency and cast some light on underlying causes.

Long memory, also known as long-range persistence, appears when the autocorrelation in return series decays hyperbolically through time. The presence of long memory is a source of market inefficiency and asset bubbles. Moreover, the degree of persistence in stock prices is also a key determinant of financial stability and can make portfolio allocation decisions sensitive to investment horizons. Although dual long memory in market return and volatility have been widely scrutinised in the finance literature, an abundance of studies neglects to account for the joint impacts of factors such as thin trading, structural breaks and inflation on the long memory. Neglecting these factors may lead to omitted-variable bias and spurious long-memory results.

To sum up, the GEM is recognised as a critical financing instrument for SMEs in Hong Kong and one of the world's most successful examples of SME stock markets. However, very limited research has been dedicated to the GEM. In particular, there is a paucity of research on the GEM's evolving market efficiency and dual long-memory components in the GEM's return and volatility. Market efficiency plays significant role in promoting effective allocation of capital to productive investments and stimulating long-term economic growth. On the other hand, the presence of long memory in market return and/or volatility instigates market inefficiency and asset bubbles, leading to the ineffective allocation of capital in the economy. In addition, while dual long memory has been largely examined, a great deal of studies fails to control the joint impacts of thin trading, structural breaks and inflation. The joint impacts of these factors may induce biased long-memory estimate and distort investment decisions.

Consequently, in the absence of such attempts, this paper aims to examine the evolution of weak-form efficiency and the joint impacts of thin trading, structural breaks and inflation on long-memory properties in both return and volatility of the GEM. The procedures of a state-space GARCH-M model, Kalman filter estimation, factor-adjustment techniques and a set of fractionally integrated models (ARFIMA-FIGARCH, ARFIMA-FIAPARCH and ARFIMA-HYGARCH) are adopted for the empirical analysis.

To the best of the authors' knowledge, this paper is the first attempt at exploring the evolving efficiency and long memory in return and volatility in a stock market for SMEs. Different from previous studies, this paper takes into account the joint effects of factors such as thin trading, structural breaks and inflation on the dual long memory.

2. Literature review

Following the random walk theory, Fama (1970) defines a market as efficient when new information is promptly and accurately reflected in its current prices. In the modern finance literature, market efficiency remains its importance for a favourable nexus between the stock market and economic growth by promoting optimal resources allocation in the economy (Lagoarde-Segot and Lucey, 2008). Fama classified market efficiency into three forms: weak, semi-strong and strong. In this paper, we focus on the weak-form version, which posits that succeeding price changes are unpredictable based on all the past trading information.

An abundance of efficiency studies has mainly focussed on testing whether a stock market is or is not weak-form efficient, assuming that market efficiency remains unchanged over different stages of market development. For example, one can refer to studies of Li and Liu (2012), Shaker (2013) and Guermezi and Boussaada (2016). However, understanding the underlying factors that lead a market to become efficient is more essential. As such, the effect of some postulated factors on market efficiency has been examined by Antoniou *et al.* (1997), Abrosimova *et al.* (2005) and Lim and Brooks (2009). Using a non-overlapping sub-samples approach, they divided the sample into sub-samples based on postulated factors such as improvements in the trading system, changes in legislative framework and the occurrence of financial turbulence. However, a major criticism of this approach lies in its assumption that the tendency towards efficiency takes the form of a discrete change in the underlying coefficient at the pre-determined breakpoint.

Prompted by this concern, a body of research employing a time-varying parameter model to depict the evolution of market efficiency has begun to emerge. Emerson *et al.* (1997) were the first to propose the state-space GARCH-M model with Kalman filter estimation to trace evolving market efficiency over time. In their model, time-varying autocorrelation coefficients are adopted to measure a continuous and smooth change in the behaviour of return series and thus the evolution of market efficiency is captured. If the market becomes more efficient through time, this smoothed coefficient will gradually converge towards zero and become insignificant. Following Emerson *et al.* (1997), several researchers such as Rockinger and Urga (2000), Jefferis and Smith (2005), Abdmoulah (2010) and Charfeddine and Khediri (2016) have proceeded to examine the evolution of stock market efficiency, applying their proposed model. These studies have widely focussed on the main boards of emerging stock markets at their early stage of development, for example, Poland, Hungary, Russia, Morocco, Egypt and Arab countries.

An extensive literature on long memory in stock market returns has begun to emerge since the 1990s. However, a great deal of long-memory studies fails to examine the joint impact of thin trading, structural breaks and inflation on long memory. There exists a number of studies reporting the effect of these factors individually on long memory. Lo and MacKinlay (1990) concluded that thin trading can cause spurious autocorrelations in return series that may result in biased long memory in the return series. Cheung (1993) postulated that a neglect of structural breaks in modelling long memory probably induces an overstated degree of volatility persistence. Long-memory pattern may be adulterated partially by the presence of structural breaks (Granger and Hyung, 2004). Cappelli and D'Elia (2006) documented that a stationary short-memory process that is subject to structural breaks shows a hyperbolic decay in an autocorrelation structure and other properties of fractionally integrated processes. Cecchetti and Debelle (2006) investigated the inflation persistence in dominant industrial economies and noted that conditional on a break in the mean, the degree of inflation persistence is much smaller than ignoring the break. Belkhouja and Boutahar (2009) reported a lower estimate of long memory in US inflation after accounting for structural shifts. Recently, Ngene *et al.* (2017) showed that the long-memory estimates for inflation-adjusted returns reduce in magnitude or in statistical significance.

3. Methodology

As noted previously, for newly established market such as the GEM, an investigation of the evolution towards efficiency is more relevant than just examining the matter of whether or not the market is efficient. Accordingly, a state-space nonlinear GARCH-M model with Kalman filter was employed to examine the market efficiency evolution. The joint effects of structural breaks, thin trading and inflation on long memory in return and volatility were also determined (as failure to account for these factors may result in biased long memory estimates). Therefore, to avoid the possibly biased long memory induced by the aforementioned factors, the GEM return series was at first adjusted for thin trading and then accommodated for breaks and inflation using factor-adjustment techniques. The adjusted returns series were sequentially fit into a set of the fractionally integrated models including ARFIMA-FIGARCH, ARFIMA-FIAPARCH and ARFIMA-HYGARCH. The econometric techniques and models employed in this study are described in the following sections.

3.1 Multiple breakpoints test

To test for multiple structural breakpoints in the mean returns, Bai and Perron (2003) approach was used. The break dates are estimated using the regression with T periods and m potential breaks as follows:

$$r_t = c_j + u_t, \quad (1)$$

where $t = T_{j-1}+1, T_{j-1}+2, \dots, T_j; j=1, 2, \dots, m+1; T_0=0; T_{m+1}=T; c_j$ is the mean of returns for each break regime. The number of breaks is identified by the sequential test of the null of no breaks ($m=0$) against an alternative $m=k$ breaks. An F -statistic to test the null of $\delta_0 = \delta_1 = \dots = \delta_{m+1}$ takes the following form:

$$\sup F_T(k, q) = \frac{1}{T} \left(\frac{T-(k+1)q-p}{kq} \right) (R\hat{\delta})' (R\hat{V}(\hat{\delta})R')^{-1} R\hat{\delta}, \quad (2)$$

where $\hat{\delta}$ is the optimal m -break estimate of δ , $(R\hat{\delta})' = (\delta'_0 - \delta'_1, \dots, \delta'_m - \delta'_{m+1})$, p represents a partial structural change and $\hat{V}(\hat{\delta})$ is an estimate of the variance covariance matrix of $\hat{\delta}$.

In addition, to identify multiple structural breaks in the unconditional variance of returns (volatility breaks), the iterated cumulative sum of squares (ICSS) algorithm which introduced by Inclan and Tiao (1994) is used. Initially, the cumulative sum of squared observations from the beginning of the residual series (ε_t) obtained from the AR(1) process of the GEM return series ($R_{2,t}$) to the k th point in time is determined as follows:

$$C_k = \sum_{t=1}^k \varepsilon_t^2, \text{ for } k = 1, 2, \dots, T. \quad (3)$$

The statistic D_k is then defined as:

$$D_k = \left(\frac{C_k}{C_T} \right) - \frac{k}{T}, \text{ with } D_0 = D_T = 0, \quad (4)$$

where C_T is the cumulative sum of squared observations for the entire sample.

When plotting the D_k against k , it is a horizontal line. If there are volatility breaks, the statistic D_k will deviate from 0, otherwise, it will oscillate around 0. When the maximum absolute value of D_k , $\{\max_k \sqrt{T/2} |D_k|\}$, is greater than the critical values obtained from the distribution of D_k , the null hypothesis of constant variance is rejected. Consequently, the k^* , which is the value at which $\max_k |D_k|$ is reached, is an estimate of volatility breakpoint.

3.2 State-space GARCH-M model with Kalman filter

To illustrate the efficiency evolution, the state-space GARCH-M(1, 1) model with Kalman filter was employed. This model allows not only for the time-varying dependency of return and volatility series on its first lagged value but also quantify the degree of volatility persistence and risk premium. It is presented in a dynamic system of space equation and state equations as follows:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 h_t + e_t, \quad (5)$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 e_{t-1}^2, \quad (6)$$

$$\beta_{1t} = \beta_{1t-1} + v_t, \quad (7)$$

where $e_t \sim N(0, h_t)$ and $v_t \sim N(0, \sigma_v^2)$.

Equation (5) is the space equation, where parameter β_{1t} represents the time-varying AR (1) coefficient and β_2 parameter represent the risk premium. Equation (6) is the state equation estimating the conditional variance of return (h_t), which is a function of the ARCH term (e_{t-1}^2) and GARCH term (h_{t-1}). The degree of volatility persistence is quantified by the sum of α_1 and α_2 . Equation (7) is the state equation capturing the dynamics of AR(1) coefficient using the Kalman filter, which is a powerful recursive algorithm developed by Kalman and Bucy (1961). Basically, the Kalman filter sequentially computes one-step ahead

estimates of the state mean and its associated standard error. The time path of β_{1t} parameter represents evolving market efficiency. Whenever it goes towards zero, it implies an improvement in market efficiency.

3.3 Adjustment for thin trading, structural breaks and inflation

Following Harrison and Moore (2012) approach, the time-varying AR(1) coefficient and the residuals were extracted from the state-space AR(1) model to adjust the returns for thin trading. This model contains Equation (3), but without the conditional variance (h_t), and Equation (5), as stated above. The de-thinned return series (r_t^d) was estimated using time-varying coefficient (β_{1t}) and residuals (e_t) as in Equation (6). The return series was then adjusted for structural breaks (r_t^{db}) using the estimated mean returns for each break regime (\hat{c}_j) and the de-thinned return series (r_t^d) as in Equation (7), as suggested by Choi *et al.* (2010). The returns adjusted for thin trading and breaks (r_t^{dib}) were further adjusted for inflation rate (i) as in Equation (8):

$$r_t^d = \frac{e_t}{1-\beta_{1t}}, \quad (8)$$

$$r_t^{db} = r_t^d - \hat{c}_j, \quad (9)$$

$$r_t^{dib} = \frac{1+r_t^{db}}{1+i} - 1. \quad (10)$$

The unadjusted (r_t) and adjusted return series ($r_t^d, r_t^{db}, r_t^{dib}$) were sequentially fitted into a set of fractionally integrated models to estimate long memory in return and volatility.

3.4 Fractionally integrated models

To model long memory in the returns and volatility, a joint model of ARFIMA (Granger and Joyeux, 1980; Hosking, 1981) and FIGARCH (Baillie *et al.*, 1996) was adopted. The ARFIMA (p, d_m, q)–FIGARCH (p, d_v, q) model is written in the following polynomial forms:

$$\Phi(L)(1-L)^{d_m}(r_t - \mu) = \Theta(L)\epsilon_t, \quad (11)$$

$$[1-\beta(L)](1-L)^{d_v}\epsilon_t^2 = \omega + [1-\alpha(L)]v_t, \quad (12)$$

$$\epsilon_t = z_t\sigma_t, \quad z_t \sim N(0, 1), \quad (13)$$

where μ is an unconditional mean; p and q are the AR and MA lag orders, capturing the short memory, $d_m \in (0, 1)$ represents the long memory in returns; ϵ_t is a white noise process; $\Phi(L) = 1 - \phi_1L - \phi_2L^2 - \dots - \phi_pL^p$ and $\Theta(L) = 1 + \theta_1L + \theta_2L^2 + \dots + \theta_qL^q$ are the AR and MA polynomials; $d_v \in (0, 1)$ measures the degree of volatility persistence; where ω is a constant; $\alpha(L) = \alpha_1L + \alpha_2L^2 + \dots + \alpha_qL^q$ and $\beta(L) = \beta_1L + \beta_2L^2 + \dots + \beta_pL^p$ are the ARCH and GARCH polynomials; v_t represents serially uncorrelated, zero-mean residuals, measured by $v_t = \epsilon_t^2 - \sigma_t^2$.

The degree of volatility persistence was also estimated using FIAPARCH model (Tse, 1998) and HYGARCH model (Davidson, 2004). Superior to FIGARCH, FIAPARCH captures the asymmetric effect in the conditional variance while HYGARCH releases the unit-amplitude restriction to account for both volatility persistence and covariance stationarity. The FIAPARCH ($p, \gamma, \delta, d_v, q$) model and the HYGARCH(p, λ, d_v, q) model can be written as:

$$\sigma_t^\delta = \omega + \left\{ 1 - \frac{\phi(L)(1-L)^{d_v}}{[1-\beta(L)]} \right\} (|\epsilon_t| - \gamma\epsilon_t)^\delta, \quad (14)$$

$$\sigma_t^2 = \omega + \left\{ 1 - \frac{\alpha(L)}{\beta(L)} \left(1 + \lambda \left((1-L)^{d_v} - 1 \right) \right) \right\} \epsilon_t^2, \quad (15)$$

where $\delta > 0$ is the power term in volatility process; $-1 < \gamma < 1$ is the asymmetry parameter; $\lambda \geq 0$ is the amplitude parameter; parameters $\phi(\alpha)$ and β represent the ARCH and GARCH terms.

4. Data

Data used in this paper are daily closing prices of the S&P/HKEX GEM Index. Data were retrieved from the Bloomberg Database for the period 3 March 2003–30 September 2017. The sample period starts from the date that the HKEX launched the index and allows us to observe the effect of the GFC and several institutional reforms undertaken by HKEX authorities during the recent decades. Also, monthly consumer price indices for Hong Kong were obtained from the IMF's International Financial Statistics and then converted into daily series using the frequency conversion technique.

The price series was transformed into return series using the logarithmic form, $r_t = \ln(P_t/P_{t-1})$, where P_t and P_{t-1} denote index closing prices at time t and $t-1$.

Table I displays the characteristics of the GEM return series during the sample period. The market return is positively skewed, indicating that the series is asymmetrical and flatter to the right compared to Gaussian (normal) distribution. The significant kurtosis implies that the return series is also leptokurtic and has sharp peaks. The Jarque–Bera joint test of symmetry and mesokurtosis further confirms the return series is non-Gaussian (non-normal) distributed. The Ljung–Box Q and Q^2 statistics up to lag 10 and 20 were highly significant, suggesting long-range dependencies in the mean and variance of the return series. The Engle ARCH statistics up to lag 5 and 10 showed the presence of conditional heteroscedasticity in the return series.

5. Findings and discussion

5.1 Detecting structural breaks

Before modelling the evolution towards efficiency and long memory, the presence of structural breaks in the GEM return and volatility series was tested using the Bai and Perron (2003) approach and the ICSS algorithm. The results consistently showed five breakpoints in the return and volatility series. The detected breakpoints appear to correspond to major pandemic, political, macroeconomic and financial events as described in Table II.

5.2 Evolving market efficiency

In this section, we investigated whether the GEM evolves towards efficiency over time, as this market has been gradually growing in terms of market capitalisation and liquidity, and the HKEX authorities have undertaken several efforts to improve the operational efficiency of the market. For this purpose, a state-space GARCH-M(1, 1) model with Kalman filter estimation was applied on daily return series of the GEM. The model, which accommodates

Obs	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque–Bera
3,601	-0.0004	0.0002	0.2707	-0.1584	0.0143	0.0480	53.84	387,761*
Q(10)	Q(20)	Q ² (10)	Q ² (20)	ARCH(10)	ARCH(20)			
113.59*	145.59*	912.01*	930.27*	70.62*	36.10*			

Note: *Indicates that Jarque–Bera statistic is significant at 1 per cent

Table I.
Descriptive statistics
of the GEM's returns

Table II.
Structural breakpoints

Breakpoint	Corresponding events	Regime period	\hat{c}_j
7 April 2006	Permission for Chinese investors to invest in Hong Kong stock markets	3 March 2003–6 April 2006	0.0004
29 October 2008	Global financial crisis	7 April 2006–28 October 2008	-0.0022
4 January 2011	H5N1 infections in humans (Avian Influenza)	29 October 2008–3 January 2011	0.0016
17 April 2013	Kwai Tsing dock strike (the world's third busiest port)	4 January 2011–16 April 2013	-0.0014
26 June 2015	Chinese stock market turbulence	17 April 2013–25 June 2015	0.0014
		26 June 2015–29 September 2017	-0.0020

Note: \hat{c}_j represents the estimated mean returns for each regime

nonlinearity and time-varying AR(1) coefficient, is capable of capturing the changing degree of market inefficiency through time and a potential tendency towards efficiency in the GEM.

As a pre-analysis step, stationarity of the daily return series was assessed to avoid the problem of spurious regression. Due to the presence of five structural breaks, the study sample was divided into six sub-samples according to six break regimes as in Table II. The six individual sub-samples were tested for stationarity using three prevalent unit root tests including the Augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP) and Ng and Perron (2001) (NP). As shown in Table III, the ADF, PP and NP test statistics unanimously rejected the null of non-stationarity at 1 and 5 per cent level of significance. Thus, the GEM return series is stationary and ready for time series model estimation.

Table IV reports results of the state-space GARCH-M(1, 1) model estimation. In the model, the intercept (β_0) represents non-measurable factors such as political events and external disturbances. Since this parameter was statistically insignificant, these factors thus have no influence on the GEM. Nonetheless, the AR(1) coefficient (β_1) at final state was significantly different from 0 at 1 per cent, implying weak-form inefficiency in the GEM. The time path of β_1 is depicted in Figure 3 and discussed in later paragraphs. While the risk premium parameter (β_2) was insignificant, ARCH and GARCH effects were significant at 1 per cent, suggesting that the GEM return volatility are highly sensitivity to past shocks. Moreover, the measure of volatility persistence represented by $(\alpha_1 + \alpha_2)$ is very close to unity (0.97), implying that undesirable shocks will persist in the long run. Additionally, post-estimation diagnostic statistics provided evidence of no serial correlation and heteroscedasticity in the standardised residuals, suggesting that the model specification is adequate.

Test	Option	Test statistic	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
ADF	C		-25.01*	-20.93*	-20.68*	-21.16*	-19.68*	-20.51*
	C&T		-25.03*	-21.46*	-20.74*	-21.29*	-19.74*	-20.54*
PP	C		-25.17*	-21.61*	-20.78*	-21.42*	-19.81*	-20.51*
	C&T		-25.18*	-21.74*	-20.78*	-21.46*	-19.85*	-20.57*
NP	C	MZ_{α}^d	-59.18*	-71.04*	-203.03*	-276.29*	-262.41*	-10.82**
		MZ_{τ}^d	-5.38*	-5.94*	-10.07*	-11.75*	-11.45*	-2.26**
		MSB^d	0.09*	0.08*	0.05*	0.04*	0.04*	0.21**
		MP_T^d	0.55*	0.38*	0.13*	0.09*	0.09*	2.53**
NP	C&T	MZ_{α}^d	-265.45*	-86.47*	-266.04*	-276.72*	-262.49*	-37.93*
		MZ_{τ}^d	-11.48*	-6.55*	-11.52*	-11.76*	-11.46*	-4.35*
		MSB^d	0.04*	0.08*	0.04*	0.04*	0.04*	0.11*
		MP_T^d	0.44*	1.15*	0.37*	0.34*	0.35*	2.41*

Table III.
Unit root tests

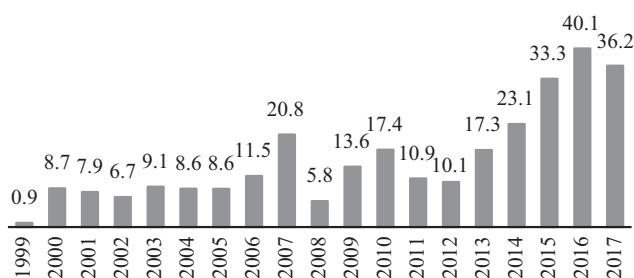
Notes: C denotes as constant; C&T denotes as constant and trend; MZ_{α}^d , MZ_{τ}^d , MSB^d and MP_T^d represents the four test statistics of the NP test. *,**Indicates that test statistic is significant at 1 and 5 per cent, respectively

Table IV.
State-space GARCH-M
(1, 1) model estimation

	Coefficient	SE	Robust-SE	t-value
β_0	0.00	0.00	0.00	-0.67
β_1 (final state)	0.11	0.02	0.02	5.86*
β_2	1.97	9.78	9.75	0.20
α_0	0.00	0.00	0.00	2.28**
α_1 (ARCH)	0.17	0.02	0.04	4.88*
α_2 (GARCH)	0.79	0.02	0.04	18.00*
$\alpha_1 + \alpha_2$	0.97			
Log-likelihood	11,039.77			
AIC	-6.13			
<i>Diagnostic statistics</i>				
$Q(10)$	37.69		$Q(20)$	53.64
$Q^2(10)$	3.84		$Q^2(10)$	5.42
ARCH(10)	0.39		ARCH(20)	0.27

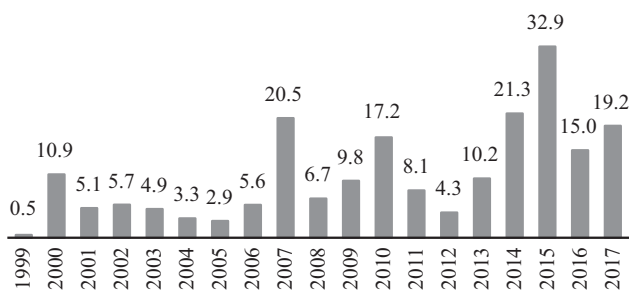
Notes: *,**Indicates that test statistic is significant at 1 and 5 per cent, respectively

Figure 3 portrays the evolution of market efficiency in GEM by showing the time path of AR (1) coefficient (β_{1t}) (red line) together with 95 per cent confidence interval (black lines), obtained from Kalman filter estimation. When the time path approaches zero, a tendency towards efficiency is implied and vice versa. As SMEs are growing rapidly and market participants and regulatory environment becomes more sophisticated over time, the GEM has been developing robustly in terms of market size (market capitalisation) and liquidity provision (trading turnover) since launch, see Figures 1–2. Increasing market capitalisation implies positive sentiments about the future prospects of the listed companies since market



Source: HKEX's factbooks

Figure 1.
GEM's market
capitalisation
(USD billion)



Source: HKEX's factbooks

Figure 2.
GEM's trading
turnover (USD billion)

capitalisation indicates how much the public is willing to pay for the companies' shares. This encourages investors to make further investments in the market and thus more transactions are executed, which in turn increase the trading turnover. Increasing trading turnover indicates more opportunities for market prices to adjust and reflect new information, thereby the degree of market efficiency will gradually improve. Additionally, institutional improvements such as improvements in system infrastructure for trading and settlement also facilitate investors' trade in the market by making the trading process more effective in terms of speed and accuracy. This in turn boosts the trading turnover and later enhances the degree of market efficiency. Therefore, the evolution of market efficiency in the GEM is now justified based on the growth of market capitalisation and trading turnover, and institutional improvements that were implemented in the GEM during the study period.

As can be seen, the GEM is still inefficient in the weak form, and the recent GFC imposed a further deviation from efficiency in the market from 2008 to 2011. However, other than this turmoil period, the GEM shows a tendency towards efficiency, which seems to align with a gradual increase in its market capitalisation and trading turnover since market launch. Growing trading turnover means that more transactions are executed, thus offering more chances for market prices to adjust and incorporate new information. This is a requisite for a stock market to be weak-form efficient. Furthermore, the tendency towards efficiency in the GEM can be supported by the efforts of the HKEX authorities to improve the operational efficiency of the market during the pre- and post-GFC period. These efforts are also referred to as institutional reforms and mainly relate to improvements in system infrastructure for trading, settlement and information dissemination, reduction in transaction fees, and measures to manage risks and market volatility (see Appendix). Specifically, HKEX upgraded the third generation automatic order matching and execution system to version 3.8, increasing the processing capacity from 3,000 orders per second to 30,000 and reducing the response time to 2 ms from 0.15 s. A major investment of US\$400m in a next generation market data platform, Orion Market Data Platform, enables the HKEX to establish points of presence for market data distribution outside of Hong Kong, such as in Mainland China. Progressive technology investments thus have boosted the HKEX's competitive appeal as a global leading fund-raising platform, which may position HKEX in the same fund-raising league as New York or London. Moreover, a recent introduction of volatility control mechanism for the securities and derivatives markets is to assure market integrity by preventing extreme price volatility stemming from significant trading errors or other unusual incidents. This initiative also offers a window allowing investors to review their strategies and the market to re-establish equilibrium point during volatile market conditions, thereby enhancing HKEX's overall competitiveness. Accordingly, the institutional reforms undertaken by the exchange authorities so far seem to be effective in driving the GEM towards weak-form market efficiency (Figure 3).

5.3 Modelling long memory in return and volatility

As mentioned previously, the GEM exposed a high degree of volatility persistence, a further examination of long-memory pattern in both return and volatility series of the GEM is desirable. To model long memory in return and volatility, long-memory parameters in the mean and variance of return series were estimated by the following three models: ARFIMA–FIGARCH, ARFIMA–FIAPARCH and ARFIMA–HYGARCH. To examine the joint effects of structural breaks, thin trading and inflation on long memory, unadjusted (r_t) and adjusted returns (r_t^d , r_t^{db} , r_t^{dbi}) were sequentially fit into these models. Initially, to obtain minimum values of Akaike information criteria, lag 2 was selected for the AR and MA terms, and lag 1 was selected for the ARCH and GARCH terms.

Table V reports the estimation results of the three indicated long-memory models. In the ARFIMA(2, d_m , 2)–FIGARCH(1, d_v , 1) model estimation, the d_m parameters using raw returns (r_t) and de-thinned returns (r_t^d) weakened in the level of significance (from 5 to 10 per cent) and

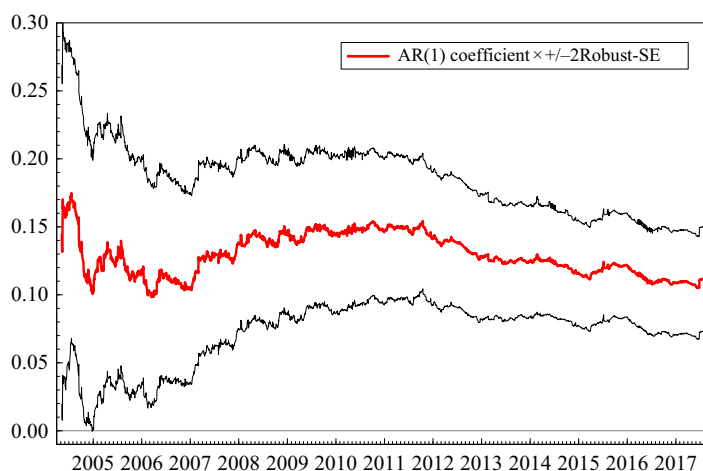


Figure 3.
Evolution of market
efficiency in GEM

magnitude (from 0.138 to 0.112). As the return series was further adjusted for structural breaks (r_t^{db}) and inflation (r_t^{dib}), the d_m parameters further declined to 0.103 and 0.100, respectively. The d_v parameters also decreased in the level of significance (from 5 to 10 per cent) and magnitude (from 0.517 to 0.481, 0.468 and 0.457) when the return series was sequentially adjusted for thin trading, structural breaks and inflation. Accordingly, the results showed evidence of the long-range persistence in the GEM return and volatility, and the persistence reducing effect of thin trading, structural breaks and inflation.

Similarly, the estimations of ARFIMA(2, d_m , 2)–FIAPARCH(1, γ , δ , d_v , 1) model revealed that the magnitude and level of significance of d_m and d_v parameters reduced steadily once the joint effects of thin trading, structural breaks and inflation were accounted for. In particular, the d_m parameter declined from 0.187 (1 per cent) to lower corresponding values of 0.153 (5 per cent), 0.112 (10 per cent) and 0.110 (10 per cent); and the d_v parameter also experience a decrease from 0.456 (1 per cent) to 0.442 (5 per cent), 0.437 (5 per cent) and 0.418 (10 per cent). Since d_m and d_v parameters remained statistically significant after controlling for the three factors, the GEM exhibited long memory in both return and volatility series, which is consistent with the estimation results of ARFIMA(2, d_m , 2)–FIGARCH(1, d_v , 1) model. Moreover, the γ parameter was significant at 5 per cent and positive (0.287), suggesting that the negative events (such as GFC and Avian Influenza, see Table II) can induce higher volatility in the GEM than the positive events.

The estimation results of ARFIMA(2, d_m , 2)–HYGARCH(1, d_v , 1) model further confirmed the presence of dual long memory in return and volatility of the GEM and the long memory reducing effect of thin trading, structural breaks and inflation. In particular, the level of significance of d_m and d_v parameters weakened from 1 to 5 per cent and 10 per cent after the factors adjustments. The degree of $d_m(d_v)$ parameters also fell from 0.124 (0.580) to lower corresponding values of 0.117 (0.472), 0.103 (0.466), and 0.100 (0.454). Table V also shows the post-estimation diagnostics in Panel C, indicating no significant serial correlation and heteroscedasticity in the standardised residuals and no sign of model misspecification for the GEM.

In addition, it is worth noting that in all three dual long-memory models, the estimates of d_m and d_v parameters using the returns adjusted for the three factors (r_t^{dibi}) fell within the interval of [0; 0.5]. This implies a stationary long memory in the GEM's return and volatility series, suggesting that the return and volatility series will revert to their means in the long term. Otherwise stated, the current market index is strongly dependent on distant past market indexes and it will revert to its long-term equilibrium after the effect of external

	ARFIMA(2, d_m , 2)- FIGARCH(1, d_v , 1)	ARFIMA(2, d_m , 2)- FIAPARCH(1, γ , δ , d_v , 1)	ARFIMA(2, d_m , 2)- HYGARCH(1, d_v , 1)
<i>Panel A: mean equation</i>			
μ	0.00	0.00	0.00
$d_m(r_t)$	0.138**	0.187*	0.124*
$d_m(r_t^d)$	0.112***	0.153**	0.117**
$d_m(r_t^{db})$	0.103***	0.112***	0.103**
$d_m(r_t^{dbi})$	0.100***	0.110***	0.100***
Φ_1	-0.860***	-1.630***	-0.859***
Φ_2	-0.969***	-0.989***	-0.968***
Θ_1	0.871***	1.632***	0.869***
Θ_2	0.976***	0.991***	0.976***
<i>Panel B: variance equation</i>			
ω	0.132*	5.379	0.212*
$d_v(r_t)$	0.517**	0.456*	0.580*
$d_v(r_t^d)$	0.481**	0.442**	0.472**
$d_v(r_t^{db})$	0.468***	0.437**	0.466***
$d_v(r_t^{dbi})$	0.457***	0.418***	0.454***
α_1	-0.184	-	-0.090
β_1	0.086	0.215	0.240
ϕ_1	-	-0.039	-
γ	-	0.287**	-
δ	-	1.300***	-
Log λ	-	-	-0.115*
<i>Panel C: diagnostics</i>			
Log-likelihood	11,037	11,070	11,057
AIC	-6.12	-6.14	-6.14
SIC	-6.11	-6.12	-6.12
Q(10)	6.84	7.15	5.96
Q(20)	12.00	12.77	11.43
Q ² (10)	2.86	3.10	2.68
Q ² (20)	3.81	3.81	3.52
ARCH(5)	0.11	0.20	0.05
ARCH(10)	0.28	0.31	0.27
P(40)	186.58*	151.66*	160.63*
<p>Notes: μ and ω are the constants for the mean and variance model; $d_m(r_t)$, $d_m(r_t^d)$, $d_m(r_t^{db})$ and $d_m(r_t^{dbi})$ represent parameters of long memory in return using raw returns, de-thinned returns, returns adjusted for thin trading and breaks and returns adjusted for thin trading, breaks and inflation, respectively; $d_v(r_t)$, $d_v(r_t^d)$, $d_v(r_t^{db})$ and $d_v(r_t^{dbi})$ represent parameters of long memory in volatility using the aforementioned set of returns; Φ_1 and Φ_2 represent AR(1) and AR(2) terms; Θ_1 and Θ_2 represent MA(1) and MA(2) terms; α_1(ϕ_1) and β_1 represent ARCH(1) and GARCH(1) terms; γ and δ represent asymmetry parameter and power terms; λ denotes amplitude parameter; P(40) indicates the Pearson goodness of fit test for 40 cells; due to space limitation, only model estimations using r_t^{dbi} were fully displayed. *, **, ***Indicates the t-statistic is significant at 1, 5 and 10 per cent, respectively</p>			

Table V.
Long-memory
model estimations

events has disappeared. Furthermore, Coakley *et al.* (2008) and Mann (2012) have placed emphasis on the important role of long memory in hedging effectiveness using various hedging models to estimate the optimal hedging ratio such as ordinary least squared model, error-correction model and fractionally integrated GARCH-type models. Therefore, our finding is highly relevant to investors in formulating their trading strategies and risk management in the sense that the dual long memory should be integrated into the hedging model for the GEM in order to estimate the optimal hedging ratio for this market.

6. Conclusion and future research

The target of this paper is to explore the evolution of weak-form market efficiency and the joint impacts of thin trading, structural breaks and inflation on long memory of return and volatility in the GEM in Hong Kong during 2003–2017. Various econometric techniques and models were employed for the empirical analysis including multiple breakpoints test to identify potential structural breaks, state-space GARCH-M model with the Kalman filter estimation to depict the evolution of weak-form efficiency, factors adjustment techniques to control the impacts of thin trading, breaks and inflation on the dual long memory and a set of fractionally integrated models (ARFIMA–FIGARCH, ARFIMA–FIAPARCH and ARFIMA–HYGARCH) to examine the long memory in return and volatility.

The results determined that the GEM is still inefficient in the weak form, yet has a tendency towards efficiency over time except during the GFC. This tendency is observed to keep abreast of the gradual increase in market capitalisation and trading turnover of the GEM since establishment. Moreover, this favourable tendency could be attributed to several institutional reforms undertaken by the HKEX authorities during the pre- and post-GFC such as improvements in system infrastructure for trading, settlement and information dissemination, reduction in transaction fees and measures to manage risks and market volatility (as described in the Appendix). Accordingly, the reforms undertaken by the exchange authorities so far appear to be effective in fostering the GEM towards weak-form efficiency.

The results also revealed the presence of stationary long memory in return and volatility series of the GEM. However, these dual long-memory properties weakened in magnitude and/or statistical significance when the returns are adjusted for thin trading and/or structural breaks. As the returns are further adjusted for inflation, the degree of long-range persistence in return and volatility series further declines. Therefore, should one fails to control for these factors, the corresponding true values would be overestimated. Additionally, the estimation of FIAPARCH process also suggests that the negative events (such as crisis and market turbulence) inflict higher volatility in the GEM than positive events. The evidence of dual long memory in the GEM can be used to assist investors in formulating their trading strategies and risk management wherein the dual long memory should be incorporated into the hedging model for the GEM to estimate the optimal hedging ratio for this market.

And finally, this paper is intended to be a proof-of-concept to provide sufficient evidence of methodological viability, which can then be used in larger scale research or replicated in new settings. It is also worthwhile to conduct an event study to assess the impacts of the GEM market development indicators and institutional reforms on the evolution towards efficiency of the GEM. Furthermore, a forecasts of the hedging model that capture dual long memory could provide investors further insights into risk management of investments in the GEM.

Note

1. H shares refer to the shares of firms that are incorporated in Mainland China and traded on the HKEX while A shares refer to the shares of Mainland China-based firms that are listed on the two Chinese stock exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange.

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(The Appendix follows overleaf.)

Table A1.
HKEX's institutional reforms to improve operating efficiency of stock markets

Date	Event
8 August 2005	HKEX introduced several improvements in clearing settlement services and nominee services, including first, a new automated mechanism enabling fund transfer through the real-time gross settlement system; second, extension of due date for corporate action instructions; and third, a reduction in handling charges for scrip fee concessions
1 October 2006	New measures to manage risks arising from securities margin trading took effect. These measures comprise: first, limits on replying; second, amendments to haircut percentage of selected financial resources rules; and third, improved transparency by disclosure
30 July 2007	Comprehensive guidance on marketing materials for listed structured products took effect. The guidance postulates that marketing materials should not be misleading or biased and should include relevant risk warnings
5 December 2011	HKEX accomplished the final phase of implementation of SDNet, which is an integrated network infrastructure for trading, clearing, settlement and information dissemination of securities and derivatives
30 September 2013	HKEX upgraded the third generation automatic order matching and execution system (AMS) to version 3.8. The processing capacity of the new system was increased from 3,000 orders per second to 30,000 and the response time was reduced to 2 ms from 0.15 s
01 November 2014	HKEX rolled out Orion Market Data (OMD) platform which provides low latency and remote distribution of market depth and products datafeed to meet diverse customer needs
22 August 2016	The 10% reduction in Securities and Futures Commission's transaction fees took effect. The fees were cut for securities transactions (from 0.0030 to 0.0027%) and derivatives transactions (from HK\$0.60 to HK\$0.54)
	A volatility control mechanism was introduced to assure market integrity by preventing extreme price volatility stemming from significant trading errors or other unusual incidents

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