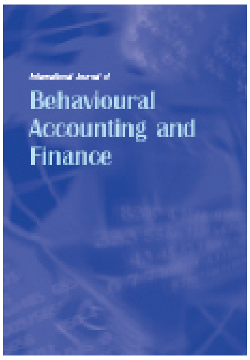

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Asia-pacific financial market inefficiency: evidence through behavioural models

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Abstract: The general equilibrium models with representative agents have proved to be inadequate descriptions of the Asia-Pacific emerging market. Within this framework, we present a model with heterogeneous agents, optimisers, and non-optimisers in which the financial markets consist of agent clusters. Our methodology consists of dividing the market participants into 'rational agents' who form sensible forecasts, and 'irrational agents' who develop biased forecasts, trade on tips, and bid prices away from their fundamental values. The analysis examines monthly frequency stock returns for the Asia-Pacific financial market and world returns using data spanning January 2004 and April 2019. Our results show a positive slope between irrationality and volatility but deterministic for return. Such a persistent connection between irrational and stock volatility suggests that investor sentiment is one of the most crucial determinants of market volatility. The ratio of successful exchange and merger depends on the proportion of the rational agents vs. the irrational ones.

Keywords: behavioural economics; asset pricing; irrationality; financial economics; Asia-pacific.

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Biographical notes: Nahed Zghidi is currently an Associate Professor at the department of Economics in Sfax Business School, University of Sfax, Tunisia. She has HDR and PhD in Economics and Master of Science degree in Economic. The current research interests include economic analysis, monetary economics, finance, and economic policy.

1 Introduction

The quest for high levels of financial market efficiency has long seemed elusive, a pertinent issue that has sparked the interest of both academics and practitioners. As perfect competition displays high levels of efficiency, it can be used as a benchmark for comparison with other market structures. It entails rational conduct on the part of buyers and sellers, full knowledge, absence of frictions, perfect mobility and perfect divisibility of factors of production, and completely static conditions (Robinson, 1960). Under certain conditions, deviant goals and rationality criteria, far from being eliminated by the process of 'natural selection', have an intense effect on market functioning. This paper rejects the idea that rationality can be defined as optimisation, based on empirical and methodological grounds in the Asia-Pacific financial market.

The detection of the relationship between heterogeneous investor behaviours (rationality and irrationality) and the market price movements is straightforward. Financial markets testify to the presence of irrationality as a behaviour resulting from the large volume of relevant information and the complex task of security analysis. This behaviour magnifies trading volumes in a subset of stocks and, hence, increases potential price volatility (Schädler and Steurer, 2019). Recent research on investors' behaviour in stock markets has shown that a tendency of traders tends to be on the same side of the market at the same time (Filip et al., 2015).

Indeed, investors are not as rational and sophisticated as we expect them to be, relying much on fads, interpersonal communication, and rumours. Irrationality is also found to be a driving force behind the dynamism of stock price. However, the different models presented are insufficient to mark the significance of the psychological bias in the price dynamic. A later in vestor belonging to a different sub-population aims at making a transaction rather than exchanging information. If irrational force occurs, returns on individual shares would be more clustered around the market returns as investors deny their private opinion in favour of the market consensus. A model with preferential attachment and deviation: the number of agents is growing within groups in the market, and a stock price will be calculated every time. Hence, a later agent either joins an existing group or acts individually following his private information. The cluster weight distribution is a power that should be considered in determining the equilibrium of each group than the general equilibrium of the whole financial market.

The paper aims to determine an asset valuation model under a microscopic vision where the percentage of rational and irrational investors according to their reasoning presents the leverage behind price formation and time to equilibrium. Our goal is also to explain the impacts of investor behaviour on stock price movements, it is invaluable to policy makers in reviewing their policies to avoid excessive fluctuations in stock markets.

The remainder of the paper is organised as follows. Section 2 presents the pertinent literature review. Section 3 describes the data and methodology escorting a brief microscopic representation of the two levers behind the price movements, namely rational and irrational traders. The results of the analysis with the empirical implication of our model are presented in Section 4. The final section concludes and offers some managerial recommendations.

2 Literature review

In a free market, prices can help allocate economic resources efficiently by signalling relevant information to economic actors (Hayek, 1945; Grossman and Stiglitz, 1980). Previous research works in finance focused on explaining the origin of the price dynamism incorporating the psychological side of the investor. Consequently, several empirical studies worldwide have investigated the connection between investors' sentiment and stock returns understand and substantiate theories of market inefficiency (Fisher and Statman, 2000; Brown and Cliff, 2004). For instance, Verma and Soydemir

(2009) found that individual and institutional investors' feelings influence the market. These findings agree with those of Chiu et al. (2018) who found a positive relationship between investor sentiment, market volatility, and macroeconomic variables. In the same vein, Zhou and Yang (2019) demonstrated that the construction of a theoretical model of stochastic investor sentiment influences investor crowdedness and affects asset prices. Gupta (2019) also found that sentiments of fund managers are a stronger predictor than returns, when it comes to forecasting volatility. Besides, Haritha and Rishad (2020) showed that irrational sentiment significantly causes excess market volatility. Hu et al. (2021) used the MS-VAR model to study the dynamic relationship among investor sentiment, stock market returns, and volatility. They found that the impact of the shock to stock market returns on investor sentiment and that stock market volatility is relatively significant. These empirical studies contradict the premises of the efficient market hypothesis that postulates that markets turn information efficient when investors behave rationally and show how irrational beliefs held by investors affect the market through asset pricing and expected returns. While our research contributes to the literature, our focus is different. As we formulate a model that assumes that an irrational trader has no inherent connection with fundamentals. Irrational traders in our model contribute to the market with rational investors. Thus, the debate evolved in two directions: While supporters of rational expectations and market efficiency propose adjustments and extensions of the standard theory, the other strand of the literature aims at providing further empirical evidence against the efficiency of stock prices and behavioural models to enlighten these phenomena. Hence, the debate has recently been restarted by the extraordinary flow of stock prices in the late 1990s. Likewise, we highlight the extensive surveys on behavioural finance by Hirshleifer (2001), Barberis and Thaler (2003) and the studies on dynamic heterogeneous agent models in economics and finance (e.g., Hommes, 2006; LeBaron, 2006 Chiarella et al., 2009; Hommes and Wagener, 2009; Westerhoff, 2009; Chen et al., 2012; Hommes, 2013; He, 2014; Chiarella et al., 2015; Zheng et al., 2017). Indeed, behavioural heterogeneity and rationality aspects differentiates our model from Barberis et al. (1998) and Daniel et al. (1998), who both presume a representative agent. First, asymmetric information leads to heterogeneous expectations among agents. Furthermore, a public signal can be interpreted differently by investors. Agents apply different 'models of the market' to update their subjective assessment based on the earnings news, which might lead them to hold dissimilar beliefs. They explore the revisions of analyst earnings forecasts around announcements, and they provide significant evidence for the hypothesis that beliefs among financial analysts are widely heterogeneous. These findings can explicate the abnormal volume of trade around earnings announcements even when prices do not change. Nevertheless, the heterogeneity of expectations might play a considerable role in asset pricing. Several models incorporating this hypothesis have been proposed. Aloulou and Ellouz (2017) focused on the impact of heterogeneous traders' beliefs and expectations on the quality of their anticipation and how it influences the process of asset price formation. They validate that heterogeneity of traders' expectations and switching affect the asset price formation process.

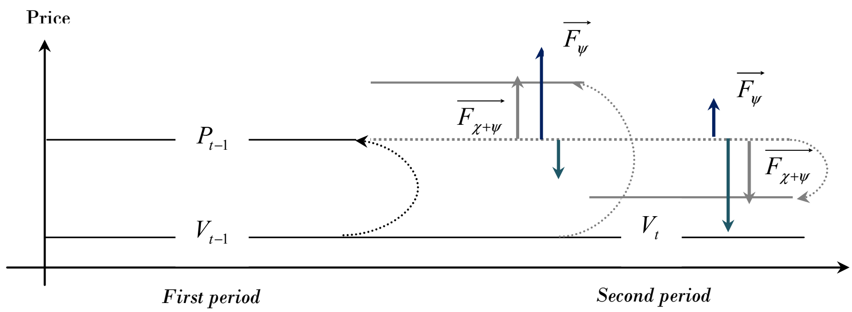
Another strand of recent literature has presented empirical evidence on market inefficiency and proposed a behavioural explanation. Hirshleifer (2001), Barberis and Thaler (2003) included extensive surveys of behavioural finance and empirical results both for the cross-section of returns and for the aggregate stock market. Much attention has been paid to the continuation of short-term returns and their reversal in the long-run. This was documented both for the cross-section of returns by De Bondt and Thaler (1985) and Jegadeesh and Titman (1993) and for the aggregate market by Cutler et al. (1991). Chiarella et al. (2015, 2017) found that the behavioural sentiment not only helps replicate most of the stylised facts simultaneously in limit order markets, but also plays a unique role in explaining these stylised facts that cannot be explained by noise trading. The study of Roberto and He (2018) outlined the state-of-art of heterogeneous agent models in finance using jointly a theoretical and empirical analysis combined with numerical analysis from the latest development in computational finance. Their work provides evidence on the explanatory power of heterogeneous agent models to various stylised facts and market anomalies through model calibration, estimation, and economic mechanisms analysis. Our methodology consists of dividing market participants into 'rational agents' who form sensible forecasts, and 'irrational agents' who develop biased forecasts, trade on tips, and bid prices away from their fundamental values. Indeed, even if risk-adjusted returns are unpredictable, irrational trading can induce substantial deviations of prices from fundamentals and cause substantial shifts in volatility. Depending on their perceptions, rational and irrational investors either pooch the price level far from its fundamental value or contribute to the mean reversion process. With the dominance of irrational traders, the former result takes place and vice versa.

3 Model specification

Although, our research contributes to the existing literature of heterogeneity of asset pricing models, our focus is different. Unlike previous works, we formulate a model that assumes that an irrational trader has no inherent connection to fundamentals. Irrational traders in our model contribute to the market along with rational ones. A fundamental matter that interests' financiers is whether a significant deviation of the asset price can be detected, controlled, and avoided. Hence, operators may find their strategies by trial, experience and error. Therefore, the market gathers agents with different utility functions and different memory spans. This heterogeneity leads either to rational decision-makers χ or to irrational ones ψ. These two forces either go in the same direction or move in opposite ones. When the market becomes more homogeneous with the dominance of irrational agents, i.e., the irrational force $\overrightarrow{F_\psi}$ becomes widely superior to $\overrightarrow{F_\chi}(\overrightarrow{F_\psi} >> \overrightarrow{F_\chi})$, the price P_t will go away from its fundamental value V_t, and crashes are inevitable. As a result, the asset price will reach its fundamental value once more and the market becomes efficient again. Nonetheless, when the force of rational investors exceeds that of irrational traders, the price deviates to approach the fundamental value and equilibrium ($V_t = P_t$) will take place step by step. The first group of investors, i.e., fundamentalists, believes that the asset price will sooner or later be driven back to its intrinsic values, while the other group, i.e., irrational traders, believes that the trend will continue. Thus, the observed price is the result of the reaction of the two poles and the models will consider the weight of each force (Figure 1).

Figure 1 The price deviations in the presence of heterogeneous beliefs (see online version for colours)

(Rational agents versus irrational ones)



The developed empirical model is intended to compare the efficiency of price discovery in the presence of heterogeneous behaviour. Within the framework of the efficiency theory, the process of price discovery is based on a macroscopic vision. Such vision foresees that in an equilibrium state, the stock return corresponds to the sum of the riskless rate plus a risky premium. The difference between the market return and the riskless rate multiplied by a risky adjustment coefficient (systematic risk) gauges this premium.

The resulting stock return as given by the efficiency theory under the acronym CAPM (capital asset pricing model) is:

$$R_{i,t} = r_f + \beta_i (R_{m,t} - r_f) \tag{1}$$

where:

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\text{var}(R_m)}$$

Fama and French (1993) implemented several empirical studies to spot the fundamental factors that enlighten average asset returns as a complement to the market beta. They underlined two important factors that characterise a company's risk: the book-to-market ratio and the company's size measured by its market capitalisation. The authors proposed a three-factor model, formulated as follows:

$$R_{i,t} = r_f + \beta_{i,m}(R_{m,t} - r_f) + \beta_{i,S} SMB_t + \beta_{i,h} HML_t + \varepsilon_{i,t} \tag{2}$$

where the factor sensitivities $\beta_{i,m}$, $\beta_{i,S}$ and $\beta_{i,h}$ are the coefficients from the time-series regression. The difference between returns on small and large stocks ("small minus big") is denoted by SMB while the difference between the returns on high and low book-to-market equity ("high minus low") is denoted by HML. Fama and French (1993) considered that the financial markets are efficient but that the market factor does not explain all the risks on its own. They conclude that a three-factor model does describe the asset returns but specify that the choice of factors is not unique. Factors other than those retained in their 1993 model also have demonstrable and demonstrated explanatory power.

When the capital asset pricing model (CAPM) draws on the hypothesis of the rationality of the investors, the model leans on the calculation of the systematic risk beta according to this perspective. In reality, the price of financial assets fits according to a heterogeneous logic based on the presence of the rational agents as well as the other irrational drilling each one a force. The sum of both forces goes either to move the price away from its intrinsic value or to converge it to this one. The divergence will be sooner or later absorbed because of the mean reversion and the price discovery process. So, the CAPM can be rewritten as the equation (2):

$$R_{i,t} = r_f + \theta_1 (R_{m,t} - r_f) \tag{3}$$

where θ_1 denotes the heterogeneous-adjusted volatility measure.

Our methodology encompasses two steps: The first consists of modelling the asset return via heterogeneous beliefs and the second of the empirical validation. We form 25 test portfolios sorted on the basis of size, book-to-market and liquidity criteria.

Our objective articulates around assessing this adjustment coefficient through heterogeneous market beliefs under a microscopic vision of the market. Since the market gathers agents with different utility functions and memory spans, the market price motion will be hardly detected. However, the heterogeneous composition of the market can be divided into two groups of participants: rational and irrational. According to this repartition, the market price is submitted to double forces: the rational and the irrational agents. Hence the weight of each category affects significantly the observed price; in the model developed below, χ denote the former, ψ refers to the latter, and the sum is equal to one. Where P_t is the observed price and V_t the unobserved intrinsic value at time t; ρ is the price adjustment coefficient estimated by the rational agents. This coefficient is a portion of the difference between the observed and the fundamental value of $t-1$. The coefficient γ is attributed to the irrational agent price adjustment. For this category of agent, the price at time t is given by an amendment of the price at $t-1$ through the coefficient γ. The fundamental value is specified as a random walk process with a drift, where the drift represents the expected growth rate of V_t.

Traders who hold 'fundamental data' about the asset price, e.g., the expected profit of a company, dividend rate, future investments, or expansion plans of a company, seek/wait for important new information and amend their orientations accordingly. They are conscious that the price oscillations will not persist for a long time. There is already a mean reversion. Therefore, the rational price equation is modelled by:

$$P_{R,t} = V_t + \rho(P_{t-1} - V_{t-1}) + \phi_t \tag{4}$$

where φ_t is a zero-mean random error with a variance $\delta^2_{\phi_t}$: $\phi_t \rightarrow iid(0; \delta^2_{\phi_t})$ and the fundamental value at t is specified as a random walk process with a drift given by:

$$V_t = V_{t-1} + m + \omega_t \tag{5}$$

where the drift, m, is measured as a continuously-compounded periodic return, and ω_t is a zero-mean random error with a variance $\delta^2_{\omega_t}$. Note that $m = E(V_t - V_{t-1})$ represents the expected growth rate of the intrinsic value V_t.

Opposite to this opinion is the idea that the fluctuations and price statistics are caused by the trading activity on the market itself, independently of the arrival of new information. The hypothesis here is that past price histories carry information about future price developments. The practitioners of this orientation are the irrational category, who attempt to predict future price trends based on historical data.

The price at time *t* relies on chart analysis techniques, i.e., only on the observed price history as a benchmark, and the behaviour of other traders as information sources. For this category, price is given by:

$$P_{I,t} = \gamma P_{t-1} + \vartheta_t \tag{6}$$

From equations (4) and (6), we can extrapolate that the irrational adjustment coefficient is superior or equal to the rational one, i.e., $\gamma \geq \rho$.

Since the market gathers the two sets $\chi + \psi = 1$, the price at any time is weighted by the percentage of each group. The following equation summarises this path:

$$P_{i,t} = \alpha P_{R,t} + \lambda P_{I,t} + \xi_t \tag{7}$$

$$P_{i,t} = \chi[V_{i,t} + \rho(P_{i,t-1} - V_{i,t-1})] + \psi(\gamma P_{i,t-1}) + \xi_t \tag{8}$$

- if $\chi = 0$, i.e.,$\psi = 1$: the market is dominated by irrational agents so, the observed price will be follows:

$$P_{i,t} = P_{I,t} = \gamma P_{i,t-1} + \eta_{i,t}$$

- if $\chi = 1$, i.e., $\psi = 0$: the market is conquered by rational agents, and the observed price will be given as follows:

$$P_{i,t} = P_{R,t} = V_t + \rho(P_{i,t-1} - V_{i,t-1}) + \phi_{i,t}$$

From the last equation, we exhibit two possible paths. If, at $t-1$ the market is efficient $(P_{i,t-1} = V_{i,t-1} + \phi_{i,t-1})$, it will be so at t $(P_{i,t} = V_{i,t} + \phi_{i,t})$ .However, if the market is inefficient at $t-1$ $(P_{i,t-1} \neq V_{i,t-1} + \phi_{i,t-1})$, it will be so at t. This inefficiency will be amortised on the tens until vanishing and a phenomenon of mean reversion will take place:

$$P_t = V_t + \rho(P_{t-1} - V_{t-1}) + \phi_t = (1-\rho)^{t-1} V_0 + \rho^t P_0 + m + \phi_t$$

The assumption $t \to \infty$ and $0 \langle \rho \langle 1$ imply $\lim_{t\to\infty}(1-\rho)^{t-1} = 0$ and $\lim_{t\to\infty}(\rho^t) = 0$

Thus, the observed price after a certain period will be expressed as:

$$P_t = m + \phi_t$$

Coming back to the general specification:

$$P_{i,t} = \chi V_{i,t} + \chi\rho P_{i,t-1} - \chi\rho V_{i,t-1} + \psi\gamma P_{i,t-1} + \xi_t$$

$$\Delta P_{i,t} = \chi(1-\rho)m + (\chi\rho + \psi\gamma)\Delta P_{i,t-1} + \mu_{i,t} \tag{9}$$

where:

$$\begin{cases} \theta_0 = \chi(1-\rho)m \\ \theta_1 = \chi\rho + \psi\gamma \\ \mu_{i,t} = \Delta\xi_{i,t} + \chi(1-\rho)\Delta\omega_{i,t} \end{cases}$$

Based on equation (9), the return for the stock *i* and the market portfolio are:

$$R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + \mu_{i,t} \tag{10}$$

And the markets return at time t :

$$R_{m,t} = \frac{1}{n}\sum_{i=1}^{n} R_{i,t} = \theta_0^{'} + \theta_m^{'} R_{m,t-1} + \mu_{m,t} \tag{11}$$

Based on expression (10), the corresponding variance is:

$$\delta_{R_t}^2 = \theta_1^2 \delta_{R_{t-1}}^2 + 2\theta_1 \delta_{R_{t-1},\mu_{t-1}} + \delta_{\mu_t}^2 \tag{12}$$

When the covariance between the stock return and the error term equals zero, expression (12) will be simplified and θ_1 will be expressed as:

$$\theta_1 = \frac{\sqrt{\delta_R^2 - \delta_{\mu_t}^2}}{\delta_{R_{t-1}}} \tag{13}$$

Since $\chi \geq 0, \psi \geq 0, \gamma \geq 0$ *and* $\rho \geq 0$.

From equations (10) and (11), the subsequent covariance between the return of a security i and the market portfolio is:

$$\begin{aligned} \text{cov}(R_{i,t}, R_{m,t}) &= \text{cov}(\theta_0 + \theta_1 R_{i,t-1} + \mu_{i,t}; \theta_0^{'} + \theta_1^{'} R_{m,t-1} + \mu_{m,t}) \\ &= \theta_1 \theta_1^{'} \text{cov}(R_{i,t-1}; R_{m,t-1}) + \text{cov}(\mu_{i,t}; \mu_{m,t}) \end{aligned}$$

$$\theta_1 \theta_1^{'} = \frac{\text{cov}(R_{i,t}; R_{m,t}) - \text{cov}(\mu_{i,t}; \mu_{m,t})}{\text{cov}(R_{i,t-1}; R_{m,t-1})}$$

Hence, the general adjusted coefficient (which is the sum of rational and irrational agents percentages, each of which is multiplied by its adjustment coefficient) of the stock return at time *t*, compared with $t-1$, is given by the substitution of $\theta_1^{'}$ as given by equation (13) in the preceding equation:

$$\theta_1 = \frac{\text{cov}(R_{i,t}; R_{m,t}) - \text{cov}(\mu_{i,t}; \mu_{m,t})}{\text{cov}(R_{i,t-1}; R_{m,t-1})} \frac{\delta_{R_{m,t-1}}}{\sqrt{\delta_{R_{m,t}}^2 - \delta_{\mu_{m,t}}^2}} \tag{14}$$

As the market volatility is given by the following expression:

$$\beta_{i,t} = \frac{\operatorname{cov}(R_{i,t}; R_{m,t})}{\operatorname{var}(R_{m,t})}$$

We can extrapolate the presence of the financial market volatility from equation (14) above:

$$\theta_1 = \frac{\beta_{i,t}}{\beta_{i,t-1}} \frac{\delta^2_{R_{m,t}}}{\delta_{R_{m,t-1}} \sqrt{\delta^2_{R_{m,t}} - \delta^2_{\mu_{m,t}}}} - \frac{1}{\beta_{i,t-1}} \frac{\operatorname{cov}(\mu_{i,t}; \mu_{m,t})}{\delta_{R_{m,t-1}} \sqrt{\delta^2_{R_{m,t}} - \delta^2_{\mu_{m,t}}}} \tag{15}$$

It can also be written as:

$$\theta_1 = \frac{1}{\sqrt{\delta^2_{R_{m,t-1}} (\delta^2_{R_{m,t}} - \delta^2_{\mu_{m,t}})}} \left[\frac{\beta_{i,t}}{\beta_{i,t-1}} \delta^2_{R_{m,t}} - \frac{1}{\beta_{i,t-1}} \operatorname{cov}(\mu_{i,t}; \mu_{m,t}) \right]$$

$$\theta_1 = \frac{\delta_{R_{m,t-1}}}{\operatorname{cov}(R_{i,t-1}; R_{m,t-1}) \sqrt{\delta^2_{R_{m,t}} - \delta^2_{\mu_{m,t}}}} \left[\beta_{i,t} \delta^2_{R_{m,t}} - \operatorname{cov}(\mu_{i,t}; \mu_{m,t}) \right]$$

From the development given below, the weighted adjustment coefficient is a function of the stock volatility at t and $t-1$, the standard deviation of the market, and its error term minus the covariance between the residues of the stocks and the market portfolio.

4 Model implications and results

4.1 Heterogeneous beliefs, volatility, and return

The difference between the observed price and the fundamental can be explained by the presence of heterogeneous beliefs. Thus, our model attempts to detect the consistency of these beliefs in this deviation.

Once a certain threshold value of chartists is exceeded, the market becomes unstable, and extreme returns occur. During these periods, prices deviate strongly from their fundamental values leading to bubbles or crashes. A previous work by Iori (2002) addressed three possibly important mechanisms of price dynamics in financial markets, namely: heterogeneity, threshold trading, and herding.

To simulate the deviation of the market price from its fundamental value, we assess:

$$P_{i,t} - V_{i,t} = \chi V_{i,t} + \chi\rho(P_{i,t-1} - V_{i,t-1}) + \psi\gamma P_{i,t-1} - V_{i,t} + \mu_{i,t}$$

$$P_{i,t} - V_{i,t} = \psi(V_{i,t} + \gamma P_{i,t-1}) + \chi\rho(P_{i,t-1} - V_{i,t-1}) + \mu_{i,t} \tag{16}$$

The difference between the observable and the intrinsic values can be explained by the inefficiency of the market in the presence of fundamentalist and noise traders.

This difference, hereafter called inefficiency premium, oscillates between two extreme boundaries according to the percentage of each category. So, the subsequent interval will be given as:

$$\lim_{\substack{\alpha \to 1 \\ \psi \to 0}} (P_t - V_t) = \rho(P_{t-1} - V_{t-1}) + \mu_t \tag{17}$$

$$\lim_{\substack{\alpha \to 0 \\ \psi \to 1}} (P_t - V_t) = V_t + \gamma P_{t-1} + \mu_t \tag{18}$$

According to equations (15) and (16), the inefficiency premium is included between the above limits as:

$$\rho(P_{i,t-1} - V_{i,t-1}) + \mu_t \leq P_{i,t} - V_{i,t} \leq V_{i,t} + \gamma P_{i,t-1} + \mu_{i,t}$$

$$P_{i,t}^R \leq P_{i,t} \leq 2V_{i,t} + P_{i,t}^I$$

$\theta_1 = \chi\rho + (1-\chi)\gamma$: The sensitivity coefficient represents a weighted average of rational and irrational investors. To explain the impact of a change in the repartition rational/irrational agents, we introduced an infinitesimal fraction $(\chi_0$ or $\psi_0)$ in the return and volatility expressions. The first case consists of varying the percentage χ of rational investor by decreasing χ_0 percentage. Thus, when the sharing of the percentage between the two categories of investor changes, the resulting stocks return will change as well.

$$\lim_{\chi \to \chi - \chi_0} R_{i,t} = (\chi - \chi_0)(1-\rho)m + \left[(\chi - \chi_0)\rho + (\psi + \chi_0)\gamma\right] R_{i,t-1} + \mu_{i,t}$$
$$= R_{i,t} + \left[\chi_0(\rho - 1)m + \chi_0(\gamma - \rho)R_{i,t-1}\right]$$

$$\lim_{\chi \to \chi - \chi_0} \theta_1 = (\chi - \chi_0)\rho + (\psi + \chi_0)\gamma = \theta_1 + \chi_0(\gamma - \rho) = \theta_2$$

When $\gamma \geq \rho, \Delta \geq 0$ so $\theta_2 \geq \theta_1$, the decrease in the rational investor percentage will generate *excess volatility* since $\theta_2 \geq \theta_1$ .Concerning the effect of this decrease on the stocks return, we distinguish two cases: either an increase or a decrease since $\rho - 1 \leq 0$, if $\frac{R_{i,t-1}}{m} \geq \frac{\rho-1}{\gamma-\rho}$. The return will increase if $\frac{R_{i,t-1}}{m} \leq \frac{\rho-1}{\gamma-\rho}$; the return will increase.

The second case aims at varying the irrational investor percentage λ by a decrease of λ_0 percentage. Thus, when the sharing of the percentage between the two categories of investors changes, the resulting stocks return will change as well.

$$\lim_{\psi \to \psi - \psi_0} R_{i,t} = (\chi + \psi_0)(1-\rho)m + \left[(\chi + \psi_0)\rho + (\psi - \psi_0)\gamma\right] R_{i,t-1} + \mu_{i,t}$$
$$= R_{i,t} + \left[\psi_0(\rho - 1)m + \psi_0(\gamma - \rho)R_{i,t-1}\right]$$

$$\lim_{\psi \to \psi - \psi_0} \theta_1 = (\chi + \psi_0)\rho + (\psi - \psi_0)\gamma = \theta_1 + \psi_0(\rho - \gamma) = \theta_2$$

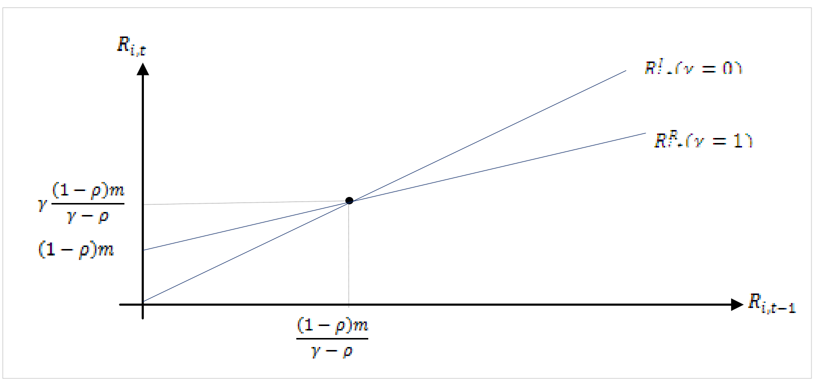
When $\gamma \geq \rho, \Delta \leq 0$ so $\theta_2 \leq \theta_1$. the increase of the rational investor percentage will *soften volatility* level since $\theta_2 \leq \theta_1$. Concerning the effect of this decrease on the stocks return, we distinguish two cases: either an increase or a decrease since $\rho - 1 \leq 0$, if $\frac{R_{i,t-1}}{m} \geq \frac{\rho-1}{\gamma-\rho}$. The return will increase if $\frac{R_{i,t-1}}{m} \leq \frac{\rho-1}{\gamma-\rho}$; the return will decrease.

According to our model implications summarised in Table 1, we extrapolate that the fraction of rational traders conforming to the fundamental strategy is negatively related to the stock volatility. However, we demonstrate a non-deterministic relationship between this fraction and the stock return. As much as the percentage of irrational traders increases, the price volatility improves. These disruptive agents follow the observed price path neglecting the intrinsic value. But in reality, the price tendency will sooner or later come back to its fundamental value.

Table 1 The relation between rational/irrational investor percentage with volatility and return

ψ	$0 \rightarrow 1$
χ	$1 \rightarrow 0$
Volatility	+
Return	±

Figure 2 The market return at *t* according to *t* – 1 in the presence of heterogeneous beliefs (see online version for colours)



where

- $R_{i,t} = \chi P_{R,t} + \psi P_{I,t} + \xi_t$: The return regarding heterogeneity
- $R^I_{i,t}$: The return according to the irrational agents, i.e., the case when $\chi = 0$
- $R^R_{i,t}$: The return according to the rational agents, i.e., the case when $\chi = 1$

The solution space**:**

To limit the space of solutions given by our model, we focus on the primitive of the return according to two explanatory variables: the return at time $t-1$ and the percentage of the rational (irrational) agents α. According to the methodology followed above (Figure 2), χ varies between 0 and 1. The return variation interval at $t-1$ is $[-c; c]$.

$$\Re_{i,t}(\chi, R_{i,t-1}) = \int_0^1 \int_{-c}^{c} R_{i,t} d(R_{i,t-1}) d(\chi) \qquad (19)$$

$$\Re_{i,t}(\chi, R_{i,t-1}) = \int_0^1 [2\chi mc(1-\rho)] d(\chi)$$

$$\Re_{i,t}(\chi, R_{i,t-1}) = \frac{1}{2} mc(1-\rho) \tag{20}$$

4.2 Estimation results

4.2.1 Database

In the global financial market, an international capital asset pricing model (ICAPM) permits the consistent expression of an asset's equilibrium expected return in any currency. For emerging markets, an international CAPM with cross-border pricing consistency is, thus, a more appropriate valuation tool than the domestic, segmented-market CAPM. One international CAPM is the nominal global CAPM, in which the single benchmark is the global market portfolio. The ICAPM applied by Jorion and Schwartz (1986), and Stulz (1995) should be a better valuation tool for internationally traded assets than the domestic CAPM. A potential candidate is the general ICAPM, pioneered by Solnik (1974), Sercu (1980), Shiller (1981) and Adler and Dumas (1983).[1]

The analysis examines a monthly magazine frequency stock return for countries, such as Shanghai stock Exchange; Stock exchange of Thailand, Bursa Malaysia, Korea Exchange, Bombay stock Exchange, Indonesia stock exchange, Pakistan stock exchange, Philippines stock exchange, and world return with data that spans the period January 2004 through April 2019. The global market portfolio is measured by the Morgan Stanley Capital International (MSCI) World Index to calculate the excess return; we use 3-month treasury bills for the Asia-Pacific emerging market. To reduce the influence of inactive and minor stocks, we omit REITs, delisted stocks, investment trusts, and stocks with inconsistent data. This process also aids in the preservation of the stock sample by removing the least liquid stocks.

4.2.2 Results

To evaluate our model, we compare it with two competing approaches, namely the ICAPM Standard and F&F three factors. In what follows, we will estimate the three models given in equations (23)–(25). We use an updated version of the dataset described in Fama and French (1993), consisting of monthly observations.

The size effect is calculated from the stock exchange capitalisation. For the book-to-market effect, we use a ratio that compares the book value of a firm to its market value. The book value[2] is calculated from the firm's historical costs or accounting value. Market value is determined in the stock market through its market capitalisation.

Our sample is composed of portfolios sorted first into five book-to-market quintiles and then into five size quintiles within the book-to-market groups. The constructed portfolios are the intersection of five portfolios formed on size (market equity (ME)) and five portfolios sorted on the ratio of book equity to market equity (BE/ME). Our methodology differs from that of Fama and French (1993) who constructed 25 portfolios using the intersection of 5 quintiles.

This sample is limited to stocks with book-to-market data in year $y-1$: considering the portfolio properties, we used year y book-to-market, averaging a cross-stocks with available book-to-market data in that year.

We calculate the monthly return at t for each stock i (including the market portfolio as:

$$R_t^i = \frac{P_t^i + D_t^i - P_{t-1}^i}{P_{t-1}^i} \quad (21)$$

We calculate the return in month t for each portfolio p (including the market portfolio) as

$$R_t^p = \sum_{i \ in \ p} W_t^{ip} R_t^i \quad (22)$$

Where the sum is taken over the stocks included in portfolio p in month t, and where W_t^{ip} are either equal weights or value-based weights, depending on the specification. Therefore, descriptive statistics of our sample as well as portfolios are depicted in Tables 2 and 3. In our model, size and book-to-market effects are incorporated directly into theta$_1$ coefficient through portfolios use. This pattern is tested against the ICAPM and F&F three factors.

Table 2 Descriptive statistic: returns of 25 portfolios formed on size and book-to-market

Portfolios	*Mean*	*Max*	*Min*	*Median*	*Std dev*
1	0.00312	0.11199	–0.23121	0.00699	0.07459
2	0.00219	0.20169	–0.09129	0.00287	0.06124
3	0.00178	0.09009	–0.11133	0.00207	0.05978
4	0.00671	0.41200	–0.36214	0.00571	0.06247
5	0.00912	0.22781	–0.24882	0.01074	0.05471
6	0.00421	0.20697	–0.42158	0.00364	0.06873
7	0.00091	0.06219	–0.19941	0.00112	0.05746
8	0.00199	0.23331	–0.10777	0.00678	0.08786
9	0.00211	0.08744	–0.01195	0.00644	0.09415
10	0.00417	0.33987	–0.41199	0.01632	0.14216
11	0.00101	0.09748	–0.20011	0.00214	0.06697
12	0.00331	0.00612	–0.00099	0.00366	0.05991
13	–0.00291	0.00026	–0.00078	–0.00331	0.06219
14	–0.00097	0.07411	–0.11669	–0.00187	0.07145
15	0.00622	0.00997	–0.01748	0.00499	0.07011
16	–0.00446	0.29962	–0.31248	–0.00651	0.04127
17	–0.00559	0.09915	–0.07455	–0.00502	0.06111
18	–0.00112	0.12578	–0.18754	–0.00200	0, 05799
19	–0.00170	0.54123	–0.39699	–0.00297	0.05889
20	0.01019	0.12995	–0.09145	0.04135	0.12163
21	0.02001	0.09125	–0.01078	0.03016	0.06541
22	–0.00412	0.24129	–0.21457	–0.00582	0.07412
23	–0.00511	0.20671	–0.34123	–0.00777	0.09078
24	–0.00111	0.16425	–0.42514	–0.01978	0.07841
25	0.00509	0.22139	–0.51298	0.00697	0.06666

Std dev: standard deviation of portfolio's return.

Table 3 Cross-sectional-regression of 25 F &F portfolios formed on size and BE/ME January 2004 to December 2019

	ICAPM		*F&F three factors*				*Heterogeneous beta*	
Portfolios	*Beta*	*R-adjusted*	b_j	s_j	h_j	*R-adjusted*	*Theta*	*R-adjusted*
1	0.971	0.12	0.881	–0.552	0.142	0.14	0.738	0.18
	(2.18)		(2.09)	(–3.12)	1.23		(2.57)	
2	1.072	0.16	0.982	0.098	–0.382	0.18	1.248	0.23
	(3.23)		(3.14)	2.12	–0.91		(5.22)	
3	1.095	0.20	1.00	0.100	–0.328	0.22	1.638	0.26
	(3.64)		(3.55)	2.27	–0.29		(7.90)	
4	0.973	0.12	0.883	–0.536	–0.541	0.14	0.785	0.18
	(2.32)		(2.23)	(–3.29)	–0.21		(2.89)	
5	1.115	0.22	1.02	–0.387	–0.285	0.24	1.77	0.37
	(3.82)		(3.73)	(–5.26)	–1.62		(8.23)	
6	0.905	0.12	0.81	–0.721	0.168	0.14	0.708	0.18
	(1.99)		(1.90)	(–2.06)	1.38		(2.18)	
7	0.975	0.13	0.88	–0.509	–0.522	0.14	–0.938	0.19
	(2.33)		(2.24)	(–3.49)	–0.36		(–3.00)	
8	1.015	0.13	0.92	–0.461	–0.469	0.15	–0.997	0.19
	(2.87)		(2.78)	(–3.84)	–0.52		(–4.01)	
9	0.981	0.13	0.89	–0.478	–0.516	0.14	0.963	0.19
	(2.48)		(2.39)	(–3.67)	–0.41		(3.09)	
10	1.065	0.15	0.975	–0.382	–0.419	0.17	1.235	0.21
	(3.19)		(3.10)	(–4.02)	–0.87		(4.43)	
11	0.963	0.12	0.873	–0.671	0.121	0.14	–0.728	0.18
	(1.99)		(1.90)	(–2.19)	1.41		(–2.26)	
12	1.047	0.13	0.957	–0.378	–0.429	0.15	1.120	0.19
	(2.97)		(2.88)	(3.79)	–0.73		(4.09)	
13	1.085	0.19	0.99	0.111	–0.369	0.21	–1.59	0.25
	(3.51)		(3.42)	2.81	–1.98		(–7.42)	
14	1.145	0.23	1.05	0.109	–0.269	0.25	1.78	0.37
	(3.88)		(3.79)	(2.96)	–1.78		(8.66)	
15	1.074	0.17	0.98	0.105	–0.374	0.19	1.562	0.23
	(3.49)		(3.40)	2.66	–1.67		(7.16)	
16	1.067	0.16	0.97	0.089	–0.408	0.17	1.236	0.22
	(3.21)		(3.12)	2.39	–1.09		(5.06)	
17	1.153	0.24	1.06	0.168	–0.241	0.25	1.78	0.48
	(4.04)		(3.95)	(3.51)	–1.95		(8.76)	
18	1.208	0.25	1.11	0.237	–0.139	0.27	2.13	0.50
	(5.16)		(5.07)	(4.19)	–2.06		(9.19)	

Table 3 Cross-sectional-regression of 25 F &F portfolios formed on size and BE/ME January 2004 to December 2019 (continued)

	ICAPM		*F&F three factors*				*Heterogeneous beta*	
Portfolios	*Beta*	*R-adjusted*	b_j	s_j	h_j	*R-adjusted*	*Theta*	*R-adjusted*
19	1.146	0.25	1.05	0.197	–0.149	0.27	1.91	0.49
	(4.22)		(4.12)	(3.77)	–2.00		(9.01)	
20	1.263	0.25	1.17	0.252	–0.101	0.27	2.25	0.51
	(6.11)		(6.02)	(4.86)	–2.18		(9.63)	
21	1.112	0.21	1.02	–0.451	–0.289	0.22	1.73	0.27
	(3.78)		(3.69)	(–4.21)	–3.07		(8.13)	
22	1.294	0.26	1.20	0.263	0.226	0.27	2.408	0.53
	(6.21)		(6.12)	(5.09)	2.77		(9.97)	
23	1.511	0.27	1.42	0.429	0.362	0.29	2.89	0.33
	(7.10)		(7.01)	(6.42)	3.19		(13.0)	
24	1.402	0.26	1.21	0.409	–0.291	0.28	2.65	0.47
	(6.84)		(6.75)	(6.33)	–2.99		(11.7)	
25	1.641	0.28	1.55	0.628	0.409	0.30	3.12	0.57
	(7.62)		(7.53)	(6.66)	3.22		(13.1)	

The t-statistic (t^*) is the average slope divided by its time-series Standard error from the month-by-month regression.

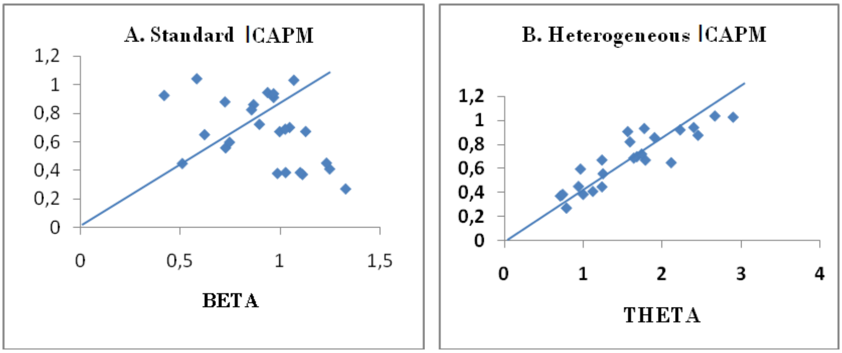
The dependent variable used in these regressions is portfolio time series average monthly excess return. Each reported coefficient is the average slope from the corresponding month by month cross-section-regressions

To emphasise the empirical validation of our model, we opt for comparing our heterogeneous pattern to the ICAPM and Fama & French three-factor model given by equations (1) and (2). Fama and French (1992, 1993, 1995, 1996) argue that size and book-to-market equity must proxy for two underlying risk factors if stocks are priced rationally.

They study the joint roles of the market, size, earnings per price ratio (E/P), leverage, and book-to-market equity in the cross-section of average stock returns. In combinations, size (*ME*) and book-to-market equity (*BE/ME*) seem to absorb the apparent roles of leverage and *E/P* in average returns. The bottom-line result is when two empirically determined variables, size and book-to-market equity, do a good job explaining the cross-section of average returns. After the publication of that paper, there was considerable discussion about whether their results were due to data dredging, whether the ICAPM anomalies they outlined would persist, or would the anomalies disappear subsequently.

To situate the stage, Figure 3 illustrates the observed risk premiums. It shows that the ICAPM fails this informal test, at least relative to the excellent performance of the Heterogeneous pattern. The best performance of the Heterogeneous model is verified in the following regressions tests.

Figure 3 Comparison of ICAPM and heterogeneous beta (see online version for colours)



A: Scatter plot of risk premium percentage against ICAPM Beta for 25 portfolios formed on size and book-to-market equity covering the period between January 2004 and December 2019.

B: Scatter plot of risk premium percentage of Heterogeneous Beta for the same 25 portfolios.

The risk premium percentage for a portfolio is the portfolio's time-series average monthly return percentage over the period. Betas are estimated and listed in Table 4.

Table 4 The evolution of theta coefficient: cross-section regressions during three sub-periods. The sample covers the period from January 2004 until December 2019 (192 months)

	Periods			
Variables	*01-01-04 to 31-12-07*	*01-01-08 to 31-12-11*	*01-01-12 to 31-12-15*	*01-01-16 to 31-12-19*
Return	–0.022	0.031	0.046	0.049
Theta	–2.121	1.619	1.223	1.879
t*	–10.541	13.002	15.162	18.02
R-adjusted	0.49	0.57	0.63	0.69
*F**	58	62.6	73.3	76.2

The t-statistic (*t**) is the average slope divided by its time-series Standard error from the period test regressions.

Cross-section regressions are used to test the three competing explanations for portfolio average excess returns. These explanations are based on equations (1)–(3). For portfolio *j* average excess returns (denoted $\overline{R_{i,t}} - \overline{r_f}$), the alternative models are: where the averages are calculated from January 2004 until December 2019.

$$\text{The CAPM}: \overline{R_{j,t}} - \overline{r_f} = \beta_{j,m}\left[\overline{R_{m,t}} - \overline{r_f}\right] + \overline{\varepsilon_{j,t}} \tag{23}$$

$$\text{The F\&F three factors}: \overline{R_{j,t}} - \overline{r_f} = \beta_{j,m}\left[\overline{R_{m,t}} - \overline{r_f}\right] + \beta_{j,S}\overline{SMB_t} + \beta_{j,h}\overline{HML_t} + \overline{\varepsilon_{j,t}} \tag{24}$$

$$\text{The Heterogeneous approch}: \overline{R_{j,t}} - \overline{r_f} = \theta_1\left[\overline{R_{m,t}} - \overline{r_f}\right] + \overline{\varepsilon_{j,t}} \tag{25}$$

The standard cross-section regression methodology is used. Estimates of betas and factor sensitivities are the aims of these regressions.

Table 3 illustrates the results of the regressions of the average excess returns on sample estimates of Heterogeneous coefficient, CAPM beta, and factor sensitivities. The coefficients for a particular model in the table are estimates of the relevant sample averages for that model described by equations (23), (24) or (25).

Each coefficient entry is also the average slope from the corresponding month-by-month Fama-Macbeth regressions, and each *t*-statistic is the average slope divided by its time-series standard error from these regressions.

The regressions in Table 3 confirm the importance of Heterogeneous Beta in explaining the cross-section of average returns. The Heterogeneous pattern strongly dominates both CAPM and the three-factor model in these regression tests.

The findings from Table 3 and the interpretation of Figure 3 permit to classify these models according to their importance to explain return.

- Heterogeneous pattern dominates both CAPM and F&F three factors.
- F&F three factors model overlooks the Standard CAPM.

4.3 Results and discussion in Asia-Pacific emerging markets

To emphasise the predominance of our methodology, we opt for *portfolios and models assessment*, i.e., a comparison between the 25 formed portfolios throughout the three patterns. If the former refers to the 'raison d'être' of portfolios sorted on size and book-to-market, the latter indicates the importance of our model compared to the nearby ones.

The cross-sectional regressions (Figure 3) show the dominance of 5 portfolios formed by companies with the largest size. These portfolios, i.e., number 5, 10, 15, 20, and 25, include the industrial sector, with the most important firms having the largest size in Asia-Pacific emerging market stocks. Portfolio number 5 dominates the other ones. Besides, having the largest size, this portfolio presents the lowest B/M value. This finding subsidises the related literature (Fama and French, 1992, 1993, 1995, 1996). Regarding B/M, portfolio number '1' overlooks number "6, 13, 7, and 8". This portfolio, even it has the smallest size, has the lowest B/M ratio.

As the two models, i.e., the CAPM betas and F&F three sensitivity factors have a common factor, we treat them jointly. *The first effect* 'systematic risk' is statistically significant for all 25 portfolios. However, we notice that the coefficient of the systematic risk of big companies is higher than the others (portfolios 5, 10, 15, 20, and 25). This allows us to conclude that big companies are more sensitive to systematic risk. Among these portfolios, number '25' exhibits the highest value (1.641) with a highly significant (-t-statistic (7.62). This result supports the component of this portfolio compared to others (number 5, 10, 15, and 20) mainly with almost all industrial and foreign companies, as these companies are too sensitive to systematic risk. *The second effect,* "coefficients of size effect", is statistically significant for both cross-sectional regression and portfolios. Nevertheless, we notice that, for both panels, the coefficient of size effect of big companies is positive (portfolios 5, 10, 15, 20, and 25). However, it is negative for the others ones, e.g., portfolio 1 with '(–0.552)' and t-statistic '(–3.12)'; portfolio 12 with '(–0.378)' and t- statistic '(–3.79)'. We validate that the five portfolios are constructed mainly by industrial and big companies (foreign companies are included). Knowing that, in the Asia-Pacific emerging market, the sample of big-size firms generally consists of industrial and banking companies, we can interpret the phenomenon according to which the size effect represents a positive effect for the banking and big companies. However, it is negative for the other ones (portfolios 1, 4, 9, 12, etc.). Finally, *the third effect*, i.e., book-to-market effect, is significant for all portfolios. Besides, book-to-market effect has a negative coefficient, which implies that this effect influences the returns negatively. In this latter that, the size effect is more than the book-to- market effect. This confirmation is due to the stability of the significance of size effect coefficients for all portfolios, and in the instability of the significance of the book-to-market effect.

The Heterogeneous cross-sectional regressions in the Table 3 elucidate the situation. Theta coefficient marks its presence significantly in the emerging markets. For all portfolios and especially according to the three ones with the largest size, the t-statistic is highly significant compared to the others (for portfolio 25, theta value equals 3.12 corresponding to t-statistic of 13.1). This coefficient as demonstrated theoretically increases with the percentage of irrational traders present in the emerging markets. Thus, the biggest companies are largely exposed to the risk of irrationality. Their presence in the market significantly drives to excess volatility. Results in Table 3 show the relation between this coefficient and return. However, we find a positive and a negative significant sign (example: portfolio '11' Theta equals –0.728 with a significance of –2.226). Our theoretical implications summarised in Table 1 exhibit these relations as follows: as the percentage of rational traders increases, volatility decreases but return can either increase or dwindle. To these theoretical repercussions, the empirical tests add the difference of sensitivity according to the size of the firm. The larger the size, the higher the sensitivity: they shed proportionally more of their employment in recessions and gain more in booms.

The lowest performance of the CAPM in explaining the cross-section of average returns corroborates the already strong empirical evidence against the CAPM (Fama and French, 2004). The empirical advantage the Heterogeneous pattern has over the three-factor model may be partly due to the way the two approaches deal with interactions between size and book-to-market effects. For example, the regression of portfolios 5 and 25 is highly significant in our model based on theta coefficient value and its adjusted R-squared value (for portfolio 25, 0.57 in the Heterogeneous model compared to 30 for F&F three-factor and only 0.28 for the standard CAPM). Interactions between size and book-to-market effects are automatically incorporated into the portfolio beta estimates in the Heterogeneous pattern. Nevertheless, the three-factor model uses separate size and book-to-market factors and so is less able to take account of such interactions.

There is another reason why the Heterogeneous model may give better results than those provided by estimating more-specialised models of expected returns. As long as the ratios of portfolio risk premiums to the market risk premium are reasonably stable over time, the Heterogeneous model ought to produce acceptable results. Such stability could have a rational or an irrational basis in the emerging markets.

4.4 Robustness: temporary validation

The dominance of our model compared to the CAPM and F&F three-factor can be due to the use of portfolio construction. The low diversification in these portfolios can slant our findings in the context of Asia-Pacific emerging market. To underline the robustness of our model, we opt for a temporary comparison using sub-period instead of portfolios. The results emphasise the theoretical implication given in *Table 1*. Our sample draws from

January 2004 until December 2019 (192 months). Thus, we subdivide this period into four sub-periods with almost 33 months each. Our results confirm the theoretical implications of our model. When the heterogeneous sensitivity coefficient increases, the stock return can either increase or decrease.

5 Conclusion and recommendations

To the current state of knowledge, the explanation of stock market behaviour raises serious theoretical problems. In this paper, we considered traders in financial markets divided into two groups: rational or irrational. Thus, each group analyses and reacts according to this criterion. In the empirical analysis, we focus on the emerging markets of the

Asia-Pacific region. Accordingly, this paper aimed to determine an asset valuation model under a microscopic vision where the percentage of rational and irrational investors according to their reasoning presents the leverage behind price formation and time to equilibrium. To validate our model theoretically, implications shows an important aspect: an increasing relation between volatility and irrational trader percentage as well as a non-deterministic sign with return.

Empirical portfolio-based validation in the context of Asia-Pacific emerging market adds another aspect to our model. In fact, the size and book-to-market criteria implicitly present in the heterogeneous pattern contribute to supporting the theoretical repercussions. Thus, the larger size increases, the higher the sensitivity of rationality. To check the robustness of our coefficient as a determinant of stock prices, we use for testing this coefficient temporary far from the space view to eliminate the impact of non-diversification hidden behind the use of portfolios. Our findings generalise the robustness of our model to explain asset movements in financial markets. They help to understand the role of non-fundamental factors in driving the Asia-Pacific emerging equity market away from a fundamentally oriented equilibrium and in influencing the risk-return perception. Our results also show a positive slope between irrationality and volatility. Such persistent connection between irrational and stock volatility suggests that investor sentiment is one of the most crucial determinants of Asia-Pacific emerging market volatility. This finding contradicts with the traditional capital market theories and supports the behavioural theories on capital markets. Herein lies the true value of the emerging field of behavioural finance, which sheds light on true financial behaviour. In this sense, this research offers highly useful information for researchers in the area of investor sentiment to advance the knowledge in the behavioural finance research field.

Some managerial recommendations are arising from these findings. First, Proper examination of the market sentiment helps investors and fund managers decide their entry and exit points for investment. Secondly, by taking the investor sentiment into account as a significant determinant of stock market volatility in asset price models, investors can enhance their portfolio performance. Finally, the results can also help policymakers' efforts to stabilise stock market volatility by grasping investor sentiment and market risk in a more specific way in order to protect investors' wealth and attract more investors.

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Notes

[1]Where purchasing power parity (PPP) is assumed to be violated.

[2]Ang and Chen (2002) calculate the book-to-market ratios as: [For a given month] the book-to-market ratio is computed using the most recently available fiscal year-end balance sheet data. As defined by Fama and French (1993), the 'book value' is measured as follows: the value of common stockholders' equity, plus deferred taxes and investment tax credit, minus the book value of the preferred stock. Therefore, the book value is then divided by the market value on the day of the firm's fiscal year-end.