

Market Efficiency in Asian and Australasian Stock Markets: A Fresh Look at the Evidence

Jae Kim,* Hristos Doucouliagos and T.D. Stanley

La Trobe University, Deakin University, and Hendrix College

Abstract

The aim of this paper is to analyze the available evidence on the efficient market hypothesis (EMH). Meta-regression analysis is applied to 1,560 estimates of the Variance Ratio test of the efficiency of Asian and Australasian stock markets. We test if there is evidence of violation of the EMH and we also explain the heterogeneity in the reported test results. Our meta-regression analysis specifically accommodates the possibility of publication selection in favor of accepting the null hypothesis of market efficiency. We find that Asian stock markets are, on average, not informationally efficient. However, market efficiency has improved over time and market capitalization and economic freedom influences stock market efficiency: more developed and less regulated stock markets are more efficient. We also find small to medium sized inefficiencies among daily and weekly returns and negative autocorrelation among monthly returns.

Keywords: Random walk, meta-regression, efficient market hypothesis

JEL Codes: G10, G14

* Corresponding author: Jae H. Kim, Department of Finance, La Trobe University.

J.Kim@latrobe.edu.au

1. Introduction

The Efficient Market Hypothesis (EMH hereafter) is one of the major theoretical predictions of finance theory. When a stock market is informationally efficient, stock prices fully reflect all available information (Fama, 1970). All freely traded stocks are then correctly priced, given expected risk and returns, as new information is instantly and fully reflected in stock prices. As a result, no arbitrage opportunities exist since excess profits cannot be made from mispriced assets. There has been considerable debate concerning the degree to which stock markets are actually efficient.¹ In light of Lo's (2005) adaptive markets hypothesis, recent studies provide empirical evidence that market efficiency is highly context dependent and dynamic and that abnormal returns can arise from time to time in response to changing market conditions (see Neely *et al.*, 2009; Lim and Brooks, 2011; and Kim *et al.*, 2011). Stock market inefficiency can arise from several sources, including structural impediments such as market manipulation (Comerton-Forde and Putniņš, 2014); poor information disclosure and communication (*e.g.*, Shamsuddin and Kim, 2010; Defusco *et al.*, 2010); and market frictions such as transaction and agency costs (Shleifer and Vishny, 1997). There may be behavioral factors that limit efficiency: for example, many investors' decisions may be dominated by fear and greed and not all investors may rationally process available information (*e.g.*, Kahneman and Tversky, 2002). In addition, underdeveloped markets, particularly those in emerging markets and transitional economies, may hinder the efficient communication of new information so that prices do not fully reflect all publicly available information.

Testing for market efficiency has attracted a great deal of attention in the literature (see, for example, Ferson *et al.*; 2005). A number of statistical tests have been developed and

¹ Traders and investors are interested in exploiting any inefficiency in stock market prices by profiting from predictable patterns. Regulators seek to make stock markets efficient because when prices reflect fundamental values they help to allocate new investments to their highest valued use.

conducted. The EMH has been tested for a large number of stock markets over different time periods. However, as the qualitative reviews by Park and Irwin (2007), Yen and Lee (2008), and Lim and Brooks (2009) document, the evidence is rather mixed and often conflicting. In this paper, we conduct a *quantitative* review of empirical results on stock market efficiency by employing the meta-analysis methodology². Meta-analysis is an effective way of drawing valid inferences from a diverse evidence base that reports conflicting findings (Stanley and Doucouliagos, 2012). It is capable of systematically exploring the differences in empirical findings, by identifying the degree to which they are driven by factors such as cross-country variations or time variations. Meta-analysis can also reveal how the systematic component of market efficiency changes as a function of economic fundamentals, such as the degree of market development and market liberalization. It can also isolate, from the systematic component, data snooping bias, sample selection bias, and measurement errors, which may be associated with individual empirical studies.

Our meta-analysis focuses on the empirical studies which use the variance ratio (VR) test of Lo and MacKinlay (1988), since it is the most popular test for market efficiency or return predictability, with highly desirable statistical properties (see Charles and Darne, 2009). The VR test also provides an appealing and natural measure for the degree of market efficiency or return predictability (Griffin et al., 2010). We focus on Asian and Australasian stock markets, including those of Australia, Bangladesh, China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Pakistan, Singapore, Sri Lanka, Taiwan, and Thailand.³ This group of stock markets has diverse characteristics, showing varying degrees of development and maturity over time. Our analysis does not cover the U.S. market, since its evolution of market

² Although widely regarded as an important tool to improve integrity and credibility of empirical research (see, for example, Cummings, 2014; and Ioannidis and Doucouliagos, 2014), the meta-analysis has not been applied extensively in the finance literature. Notable meta-analytic studies in finance include Capon et al. (1990), van Ewijk et al. (2012), and Fernandes et al. (2014).

³ This choice is driven by the Asian countries analyzed in the primary literature.

efficiency for the past 100 years is well-documented in the literature (e.g. Gu and Finnerty, 2002; and Kim *et al.*, 2011). Our study is the first meta-analytic study of market efficiency based on empirical results from a cross-section of emerging and developed stock markets.

The main findings from our meta-analysis are summarized as follows. We find violation of the EMH for Asian and Australasian stock markets, with stock market inefficiency being higher, in general, for the countries with the least developed and more regulated stock markets. Importantly, we also find that stock market efficiency has improved over time. We also find that data frequency matters. Specifically, there are small to medium sized inefficiencies among daily and weekly returns and negative autocorrelation among monthly returns.

The paper is set out as follows. Section 2 provides a brief review of market efficiency and presents the details of the VR test. In section 3 we discuss the meta-regression methodology and its attractive features, especially in the context of testing for market efficiency. Section 4 discusses the details of the data used in the meta-analysis, and Section 5 presents the results of the meta-regression analysis. Section 6 concludes the paper.

2. Stock Market Efficiency and the Variance Ratio Test Statistic

In this section, we provide a brief review of the recent literature on stock market efficiency and present the variance ratio test statistic as a measure of the degree of market efficiency. We also discuss its usefulness and limitations as a measure of market efficiency.

2.1. Brief review of stock market efficiency

When a stock market is efficient, prices adjust instantaneously and accurately in response to new information. According to the EMH, all publicly available information is fully reflected in stock prices, and no market participants can systematically make abnormal profits (Fama, 1970). When the information set is limited to past prices and returns, the market is said to be

weak-form efficient, where the current price reflects all available information from past price history. Whether a stock market is efficient in the weak-form has been a highly contentious issue in finance. While most finance academics believe in weak-form efficiency (Doran *et al.*, 2010), predictable patterns of stock returns have been widely observed. For example, Jegadeesh and Titman (1993) document strong momentum effects; and behavioral finance researchers recognize that investor behavior such as overreaction and overconfidence can cause systematic departure from efficiency (*e.g.*, De Bondt and Thaler, 1985; and Barber and Ordean, 2001).

The accumulated empirical evidence is rather mixed and conflicting. In their historical survey, Yen and Lee (2008) report empirical findings in support of market efficiency in the 1960s, “mixed evidence” in the 1970s and 1980s, and “refuting evidence” in the 1990s. Park and Irwin (2007) present a survey with similar findings in the context of the profitability of technical trading rules. Harvey (1995) observes that stock returns of emerging markets are generally more predictable than those of developed markets, possibly due to their segmentation from global capital markets. In contrast, Griffin *et al.* (2010) provide evidence that stock returns in emerging markets are as unpredictable as those of advanced markets. With these highly mixed empirical results, stock market efficiency remains one of the most controversial and contested hypothesis in finance.

The EMH also has strong implications to practitioners, investors, and regulators. There is an enormous industry based on the technical analysis of stocks and commodities, with numerous trading strategies employed by traders⁴. Moreover, many mutual fund managers try to outperform the market and claim that they have done so. The EMH has also found its way into securities litigation (*e.g.*, Fischel, 1989 and Cornell and Rutten, 2006). These are all in

⁴ According to the bestseller, “Flash Boys,” large banks are making billions by placing their program trading computers physically closer to the New York Stock Exchange’s computer (Lewis, 2014).

large part inconsistent with the EMH. On the other hand, there are arguments that these observations against the EMH are in fact spurious. For example, Bender et al. (2013) argue that technical analysis rules might reflect imperfectly rational noise trading and stock chart patterns might just be “illusory correlations”. Zhang and Jacobsen (2013), find that monthly seasonal effects may not be real, as they could be subject to data snooping bias, noise, and sample selection bias.

As a compromise between the efficient market hypothesis and its behavioral critics, Lo (2004) proposes the *adaptive markets hypothesis*. One of its implications is that market efficiency is highly context dependent and dynamic; and that abnormal returns can predictably arise from time to time due to changing market conditions. Lim and Brooks (2011) provide a comprehensive review of recent empirical studies in the weak-form efficiency of stock market, which strongly support the time-varying nature of return predictability. Kim *et al.* (2011) examine the case of the US stock market over 100 years and provide empirical evidence that return predictability changes over time depending on prevailing market and economic conditions. Based on a cross-sectional study of more than fifty stock markets, Shamsuddin and Kim (2010) find that return predictability depends on a number of measures for equity market development. Hence, the extant literature on the empirical testing of the weak-form market efficiency of stock market holds the view that the degree of market efficiency changes over time depending on economic and market conditions surrounding the market. The latter includes a range of factors such as market fundamentals, regulations, trading technologies, psychology of market participants, political landscape, and the state of the economy.

2.2 Variance ratio as a measure of stock market efficiency

As Grossman and Stiglitz (1980) theoretically demonstrate, a perfectly efficient market is not possible. Since Campbell et al. (1997) proposed the notion of relative efficiency, the research

focus has moved to measuring the degree of relative efficiency from testing absolute market efficiency. While there are alternative measures of relative efficiency (Griffin et al., 2010), the variance ratio (VR) test of Lo and MacKinlay (1988) is the most popular and appealing, based on autocorrelations of returns⁵. While there have been a number of improvements and extensions (see Charles and Darne, 2009), the test is essentially based on the statistic as a ratio of the variance of k -period stock returns to one-period returns, which can be re-written as a function of return autocorrelation as follows:

$$V(k) = 1 + 2 \sum_{j=1}^{k-1} \left(1 - \frac{j}{k}\right) \rho_j, \quad (1)$$

where ρ_j is the autocorrelation of asset returns of order j . By construction, $V(k)$ is one plus the weighted average of autocorrelations up to order $k-1$, with positive and declining weights. The main attraction of the VR statistic over its alternatives is that it provides an estimate of the size of return autocorrelations, as well as its overall sign. A value of $V(k)$ greater (less) than 1 indicates the presence of overall positive (negative) autocorrelations up to the order $k-1$. Due to this property, $V(k)$ is widely used as a measure for the degree of market efficiency or return predictability (*e.g.*, Griffin *et al.*, 2010; Kim et al., 2011).

To evaluate market efficiency or the presence of return predictability, researchers test for $H_0: V(k) = 1$, implying that all autocorrelations (ρ_j s) to order $k-1$ are zero. When $V(k) = 1$, stock returns are not predictable from their own past. To test $H_0: V(k) = 1$, Lo and MacKinlay (1988) propose the test statistic:

$$M(k) = \frac{\hat{V}(k) - 1}{se(\hat{V}(k))}, \quad (2)$$

⁵ Other autocorrelation-based tests include Box-Ljung type tests (*e.g.*, Escanciano and Lobato, 2009), spectral tests (*e.g.*, Escanciano and Velasco, 2006), and non-parametric tests (*e.g.*, Wright, 2000). The variance ratio test is more widely used in the empirical literature, as it possesses better small sample properties (see Charles et al., 2011).

where $\hat{V}(k)$ is the sample estimator for $V(k)$ and $se(\hat{V}(k))$ represents the standard error of $\hat{V}(k)$. Note that Lo and MacKinlay (1988) propose two versions of the above test statistic. The first version (denoted $M_1(k)$) is valid when the asset returns are generated from an identical and independent distribution (i.i.d); and the second version (denoted $M_2(k)$) is valid when the asset returns follow a martingale difference sequence (MDS). This test allows for asset returns with a general form of conditional or unconditional heteroskedasticity, widely observed in asset returns. Note that the two statistics are different only in the form of standard error estimators. Lo and MacKinlay (1988) show that $M_1(k)$ asymptotically follows the standard normal distribution under i.i.d. asset returns, and so does $M_2(k)$ under the MDS.

As mentioned earlier, our meta-analysis exploits sample estimates of $\hat{V}(k)$ reported in the past empirical studies. However, we note that the VR statistic has some limitations as a measure for the degree of market inefficiency. First, it does not capture the effects of the costs associated with transactions and gathering information (Griffin *et al.* 2010; Section 6), which can be high in emerging markets and dissimilar across different international markets. Second, the measure may contain noise from market microstructure and nonsynchronous trading (Boudoukh *et al.*, 1994). Griffin *et al.* (2010) warn that caution should be exercised when VR values are directly compared across different international markets. On these points, we argue that meta-analysis is an effective way of isolating noise and various biases from the fundamental component of the VR estimates and it facilitates their comparison in a systematic way. That is, it controls the systematic component of VR estimates over time and across different international markets, isolating the noise and non-fundamental components of VR estimates, including the effects of potential publication bias. For example, the effect of declining transaction and information costs that stock markets have experienced since the 1990s may not be captured in the VR estimates reported in individual studies: however, it can be revealed in a meta-regression with the VR estimates showing a downward trend over time.

The VR estimates from two dissimilar markets during different time periods may not be directly comparable, but their responses to the market fundamentals such as the market capitalization can be analyzed in the framework of meta-analysis.

Various market microstructure factors, such as the level of liquidity, cost of trading, and speed of information incorporation, are important for the degree of market efficiency. While there are methods indirectly measuring the degree of liquidity (see Lesmond et al, 1999; Amihud, 2002), we are limited by data availability since these measures require the use of daily volume or transaction costs. However, as Lagoarde-Segot (2009) reports from an extensive empirical analysis of emerging markets, higher market capitalization decreases both transaction costs and illiquidity levels. In addition, Lagoarde-Segot (2009) finds that the degrees of market microstructure in emerging markets are time-varying, strongly related to one another depending on economic and political contexts such as financial industry development and institutional reforms. On this basis, we use market capitalization and economic freedom as proxies for the economic fundamentals which control the degree of market microstructure factors, also paying attention to the variation of the VR estimates over time.

Conrad and Kaul (1988) argue that autocorrelation in stock returns represents time variation of expected returns. However, their model depends heavily on its parametric structure and their result may not be robust to different model specifications. For example, if their model is specified with a constant expected returns allowing for time-varying return predictability, the observed autocorrelation can be regarded as a reflection of market inefficiency. In addition, according to Fama and French (1988a), time-varying equilibrium of expected returns occurs over long horizons, such as 3 to 5 years. We note that the VR test is widely used as a test for short-horizon return predictability, with the value of holding period k typically set to far less than 1 year. It is well-known that the test is not suitable for long-horizon analysis, since the VR

statistic is severely biased estimator for $V(k)$ and the test shows undesirable small sample properties when the value of holding period k is high (see, for example, Chen and Deo; 2006).

3. Meta-regression Methodology

The key challenge behind all empirical analyses is making valid inference. Meta-regression analysis (MRA) has been developed to meet this fundamental challenge (Stanley and Doucouliagos, 2012). We employ meta-regression to achieve three tasks: (1) to formally test the EMH, (2) to analyze the distribution of the reported estimates and identify the factors that drive heterogeneity in this literature, and (3) to identify and correct potential publication selection bias. MRA can concurrently inform on each of these dimensions.

3.1 Publication selection

There is much evidence to suggest that researchers often have a preference for reporting empirical results that conform to researcher beliefs and suppress evidence that is at odds with these preferences (Roberts and Stanley, 2005; Stanley and Doucouliagos, 2012). Reported estimates may then be a biased sample of all estimates, potentially resulting in erroneous statistical inferences. Hence, it is important to test for publication selection bias and accommodate potential bias should it be present in the research record. Following Stanley and Doucouliagos (2012), we apply the so-called Funnel-Asymmetry Test Precision-Effect Test (FAT-PET) meta-regression model:

$$VR1_{ij} = \beta_0 + \beta_1 se_{ij} + \varepsilon_{ij}, \quad (3)$$

where $VR1_{ij} = \hat{V}(k) - 1$ ($VR1_{ij}$ is the i th variance ratio minus one reported in the j th study), se_{ij} is its standard error, and ε_{ij} denotes the usual regression error term.⁶ See Stanley (2008) and Stanley and Doucouliagos (2012) for further details on this model.

Stanley and Doucouliagos (2012 and 2014) suggest that a more accurate estimate of the underlying effect corrected for publication selection bias can be derived by replacing se_{ij} by se_{ij}^2 . Doing so gives the precision-effect estimate with standard error (PEESE) model:

$$VR1_{ij} = \alpha_0 + \alpha_1 se_{ij}^2 + v_{ij}. \quad (4)$$

The logic behind the FAT-PET is as follows. When an empirical literature is free of publication selection bias, then the estimated effect sizes (say VR estimates) will not be correlated with their standard errors (Egger *et al.*, 1997; Stanley and Doucouliagos, 2012). In fact, the validity of regression's conventional t-test requires this independence. In contrast, if researchers search for estimates that are statistically significant (*e.g.* a rejection of the EMH), they will re-estimate their models until they achieve some 'acceptable' level of statistical significance (*e.g.*, statistical significance at the 5% or 10% level).⁷ This selection will generate a correlation between an estimated effect and its standard error and will result in a truncated or asymmetric distribution of reported VR estimates (Stanley, 2008). Hence, a test of $\beta_1 = 0$ (known as the FAT or Funnel Asymmetry Test) provides a test of the existence of asymmetry in the estimates and publication selection and the $\beta_1 se_{ij}$ term reflects the impact of publication selection bias. A test of $\beta_0 = 0$, known as the PET or Precision Effect Test, provides a test of the overall existence of market inefficiency in the research record, corrected for publication

⁶ Throughout the paper we measure the effect size as $VR - 1$, rather than VR , which we denote as $VR1$. This is for expositional purposes only. The inferences are *identical* if we use VR instead of $VR-1$, when properly interpreted.

⁷ In the case of the EMH, re-estimation can involve taking different samples, time periods, countries, indices, *etc.*

selection. Also, the estimate of α_0 provides an estimate of the degree to which markets are inefficient.⁸

Although the FAT-PET-MRA model remains the foundation of the tests investigated here, application to variance ratios introduces new challenges. In particular, the variance ratio is known to have small-sample bias (Lo and MacKinlay, 1988), and publication selection may ‘go both ways.’ Typically, selection bias in empirical economics is in favor of rejecting the null hypothesis of a zero effect (Card and Krueger, 1995; Doucouliagos and Stanley, 2014). In such cases, authors do not report all of the results they uncover. Rather, they select results that are consistent with their prior expectations, conventional theory, or results which they believe have a stronger chance of being published. The effect of this process is that certain findings may be suppressed while others are over-represented. Consequently, publication selection bias may tend to overstate the evidence against the EMH. This could happen if *some* researchers have a prior that the market is inefficient and experiment with their models, data, and methods to find a variance ratio that differs from 1 (either greater than 1 or less than 1). However, other researchers may believe that investors are rational and markets are efficient and dismiss some large variance ratios as faulty. In this case, evidence that rejects the null may go unreported. That is, there may be selection in this research literature in both directions: for statistical significance (rejection of EMH) and for statistical insignificance (acceptance of market efficiency). *A priori*, it is not possible to predict the net direction of this bias or whether any net bias is likely to remain. This is an empirical matter about which meta-regression analysis can inform.⁹

⁸ Recall that we use VR -1. Hence, the test of the EMH is the null of $\beta_0 = 0$. If we used VR, then the test of the EMH involves the null of $\beta_0 = 1$.

⁹ Ed Tufte (2006, p.687) famously remarked that t-statistics that fall in the range between 1.6 and 2 lie in the “Zone of Boredom, Ambiguity, and Unpublishability”.

An additional complication arises because even in the absence of reporting or publication selection, small-sample bias will cause the effect size, VRI ($=VR-1$), to be correlated with its sample size and thereby inversely with its own standard error. The conventional FAT-PET-MRA (equation (3)) may therefore be affected by this small-sample bias.

Given the above concerns with conventional meta-analysis, we conducted simulations for meta-regression models of the variance ratio tests to accommodate possible publication selection bias. Appendix A provides details of the simulation design and results. The central purpose of these simulations is to investigate the statistical properties of PET for the application to the EMH and thereby insure the validity of our MRA methods in assessing this literature's evidence of market efficiency. Past simulations (*e.g.* Stanley 2008) have only reported the performance of these MRA models of publication bias when there are various incidences of selection for statistical significance—not when selection is for statistical *insignificance*. This too may potentially invalidate the FAT-PET-MRA by adding a yet another correlation of the reported effect to its standard error. Our simulations suggest that using a larger critical value, 3.5, instead of the normal critical value of 1.96 will accommodate both small-sample bias as well as potential selection for insignificance— see Appendix A for details.

3.2 *Heterogeneity*

Eqn. (3) can be extended to explain observed variation in the variance ratio test.

$$VR1_{ij} = \beta_0 + \beta_1 se_{ij} + \sum \beta_k Z_{kij} + \varepsilon_{ij}, \quad (5)$$

where Z_k represents variables coded from the studies themselves and exogenous variables on market capitalization and economic freedom coded by us from public information. Other examples of Z -variables include: country, level of development, holding period, and data frequency. See Table 3 below for a full list and description.

3.3 Estimation

Eqns. (3) to (5) are estimated by weighted least squares (WLS) in order to accommodate differences in the variances of the VR estimates across studies. Optimal weights for WLS are given by the inverse variance (Hedges and Olkin 1985). For most of the analysis we use $w = 1/se_{ij}^2$. However, for robustness we also use *random* effects weights, $w = 1/(se_{ij}^2 + \tau^2)$, where τ^2 is the between-study or heterogeneity variance. Stanley and Doucouliagos (2017) demonstrate that WLS MRA is superior to both conventional fixed- and random-effects multiple MRA because WLS MRA has lower bias and mean squared error if there is publication bias and is practically equivalent to random-effects when there is no publication bias.

As can be seen from Table 1 below, we employ multiple estimates from the same study. Dependence within studies is often an issue in meta-regression analysis and can result in downward bias in meta-regression analysis standard errors (Moulton 1990; Cameron, Gelbach and Miller 2008; MacKinnon and Webb 2013). However, it is worth noting that tests of the EMH are different to most empirical research in economics. A common feature of empirical economics is that authors typically estimate numerous versions of a given econometric model: this typically involves alternate specifications, estimators and data samples. This dimension for experimentation and selection is not available to VR tests of the EMH. For example, there can be no specification searching for alternate control variables, which ordinarily generates much excess variation in reported empirical estimates in other areas of economics research. Here, we have multiple estimates but these should be largely statistically independent. For example, authors often report VR tests for several countries, and estimates for different countries can be considered to be statistically independent (Hunter and Schmidt, 2004). Variance ratio testing involves application of a specific formula, and there is little scope for experimentation with alternate specifications, functional forms and estimators. Nevertheless, there are still design

choices made by authors, including the choice of countries to analyze, the time period studied, and the holding period for the VRT. Among the VR tests that we find, the intraclass correlation is 0.251, suggesting that there is actually a significant degree of dependence. Hence, we take the potential for data dependence into account by estimating hierarchical models and panel data models that accommodate data dependence.

4. Quantifying the Research Record on Market Efficiency

The search for studies and data coding followed the MAER-NET guidelines for meta-regression analysis (Stanley *et al.* 2013). Specifically, we conducted a comprehensive search for studies that tested the EMH for Asian and Australasian stock markets. Numerous search engines were used: Econlit, Google Scholar, Academic Search Complete, Business Source Complete, Science Direct, Scopus, Web of Science, and Wiley Online Library. Keywords used included ‘variance ratio’, ‘efficient market hypothesis’, ‘random walk’, ‘predictability’, ‘stock markets’, ‘market efficiency’, and ‘market inefficiency’. In addition, we pursued cited references from studies, and we also physically checked numerous economics, finance and accounting journals. The database searches were terminated June 2014.

The empirical literature on the EMH is enormous. In order to make sense from a diverse literature with diverse findings, it is essential to construct a set of comparable estimates. Our criteria for inclusion were as follows. First, the study had to report an estimate of the variance ratio. There are other tests that explore the EMH. However, in order to ensure comparability, only those that report estimates of VR are included in our dataset. For example, we do not consider studies on the predictability of stock returns using macro variables. Second, the study had to report an estimate using Asian or Australasian data. Some studies report estimates also for other countries. These estimates are excluded from the meta-analysis. Third, the study had to be published. Some researchers prefer to include the so-called ‘grey literature’, such as

working papers and doctoral thesis. Others prefer to stick to the published literature.¹⁰ Fourth, for practical reasons, we exclude any study that was not written in English. Fifth, we focus on overall market efficiency and thereby exclude any estimates for individual stocks to avoid potentially overwhelming volatility and unreliability, particularly if individual stocks in emerging countries experience thin trading: aggregate indices are less vulnerable to thin trading. Also, testing efficiency of individual stocks is likely to be statistically less powerful, since no account is taken of cross stock correlations. Finally, we exclude estimates from multiple variance ratio tests (MV) as we cannot normally recover VR values from the MV statistic and the MV test statistic does not have a standard error estimator. In addition, it is difficult to justify an MV statistic as an appealing measure of predictability.

This search process identified 38 studies that report a variance ratio for Asian or Australasian stock markets. Although other tests statistics are reported in the research literature, the variance ratio test is by far the most prevalent. However, only 29 report sufficient information from which we could calculate the standard error of the VR.¹¹ The standard error is necessary in order to explore whether the EMH literature is afflicted by publication selection bias and it is also needed to properly weight the reported findings. Many studies report only the statistical significance of the VR without reporting the associate standard errors. The 29 studies report a total of 1,560 VR estimates.¹² We make only one further adjustment to the quantifiable relevant empirical record—outliers. 14 estimates have an absolute value of the standardized residual greater than 3.5 from the FAT-PET, Eqn (3), and these outliers are

¹⁰ It is often claimed that including unpublished studies reduces or even eliminates publication selection bias. Stanley and Doucouliagos (2012) argue that this belief is mistaken.

¹¹ Some studies focus only on the statistical significance of the VR but do not report standard errors. The results from these studies are broadly in line with our own findings.

¹² The full dataset can be download for replication and extension from www.deakin.edu.au/meta-analysis.

removed from further statistical investigation.¹³ The 1,560 estimates used in our study are the population of comparable VR estimates for Asia and Australasia. While these come from 29 studies, the sample size is large. Moreover, our analysis makes use of 92 statistically independent samples. Hunter and Schmidt (2004) show that samples from different countries can be treated as being statistically independent, even if analysis of such samples is reported in the same study. In other words, the 29 studies can effectively be treated as 92 distinct cases that report 1,560 estimates of the EMH. Consequently, we have a high degree of confidence in the quality of the sample for inference purposes.

In addition to collecting data on the VR and its standard error, we also coded several other study characteristics (see Table 3 below). Two of the authors coded the studies and then checked each other's coding. All included studies are referenced in Appendix B.

Table 1 lists the studies that form our meta-analysis dataset, including the countries studied and the number of estimates from each study. The first study was published in 1992 (Lee) and the two most recent studies in 2013 (Guidi and Gupta and Youssef and Galloppo). Table 2 presents the country distribution of the estimates and the average value of the VR for each country.

Tables 1 and 2 about here

Figure 1 presents the *VRI* estimates in the form of a funnel plot, illustrating the association between *VRI* and its precision, where precision is measured as the inverse of *VRI*'s standard error. The funnel plot is a convenient way of illustrating the distribution of the reported findings. It can highlight outliers and influential observations and it can also, potentially, highlight publication selection bias (see Stanley and Doucouliagos, 2010, 2012). Estimates that

¹³ We also removed a single extreme value with a very large VR1 (in excess of 8) that was estimated with poor precision.

stand out are potentially leverage points or outliers. Severe selection bias would cause a noticeably asymmetric distribution of results.

Figure 1 about here

The funnel graph reveals a long tail of relatively high *VR1* values, even after the very large positives *VR* values are removed. Asymmetry in effect sizes is typical of meta-data sets, and it is often an outcome of publication selection bias and/or heterogeneity inherent in different samples (Roberts and Stanley, 2005; Stanley and Doucouliagos, 2012). Figure 1 suggests that publication bias might be an issue in this literature, with the long tail suggesting preference for reporting violation of the EMH.

About 21 percent of the estimates report a *VR1* less than 0 and the remainder (about 79 percent) report a *VR1* that is greater than 0. The weighted-average *VR1* is 0.13; this value is shown as the vertical line in the figure.

Table 3 lists the variables used in the multiple MRA. Some are dummy (0/1) variables (*Weekly*, *Monthly* and the various country dummy variables), while others are continuous (*Standard error*, *Average year*¹⁴, *Holdingperiod*, *MarketCap* and *EcoFreedom*). The binary variables *Weekly* and *Monthly*¹⁵ reflect the data frequency used (with daily as the base). We also include the length of the holding period *k* used to construct the *VR*; recall Eqn. (1). The time horizon can potentially inform on the degree of predictability.¹⁶ These three variables, *Weekly*, *Monthly* and *Holdingperiod*, are included in the MRA to capture potential differences

¹⁴ In unreported regressions we also included a dummy for the Asian financial crisis, assigning a value of 1 for estimates that relate purely to the post-financial crisis period. This variable was never statistically significant in any of the MRA models.

¹⁵ Of the 1,560 *VR1* estimates included in our sample, 434 relate to monthly data and 526 relate to weekly data, with the remainder relating to daily data. We include in *Monthly* 13 observations for quarterly returns and 11 observations for annual returns.

¹⁶ We also calculated this length as fractions of monthly data, *i.e.*, the length of the holding period for weekly and daily frequencies was converted into monthly. For example, $k=20$ for daily data is converted into a one month holding period.

in predictability of investment horizons. Stock price predictability may increase with the investment horizon as has been reported in some prior studies (*e.g.*, Fama and French, 1988b). In particular, by applying the *VR* test to U.S. stock return, Poterba and Summers (1988) report negative serial correlation in the long horizon and positive serial correlation in the short horizon.

Table 3 about here

As noted earlier, the *VR* can be estimated assuming either homoscedasticity or heteroscedasticity. The difference affects only the calculation of the standard error and not the value of the *VR* or *VR1*. Hence, we do not include this research design choice in the MRA as a moderator variable.¹⁷ *Average year* is included to investigate whether the reported *VR* estimates have been changing over time. Generally, if stock markets are becoming more (less) efficient over time, then the expected or fundamental component of *VR* should be falling (rising).¹⁸

Finally, we explore the effects of the degree of market capitalization and the degree of economic freedom prevalent in the countries and time periods sampled.¹⁹ As discussed earlier, we use market capitalization as a proxy for the level of market microstructure factors. We use economic freedom as a proxy for economic and political factors which drive financial industry development and institutional reforms. Market capitalization data was collected from the World Bank Development Indicators and from individual stock exchanges. Data on economic freedom was collected from the Fraser Institute (Economic Freedom of the World).²⁰

¹⁷ If a dummy variable for heteroscedastic *VR* estimates is included in the MRA, it is never statistically significant.

¹⁸ An exception to this interpretation occurs if the variance ratio tends to be less than one, as we find among monthly frequencies.

¹⁹ Market capitalization and economic freedom are highly correlated with a correlation coefficient of 0.85. Hence, we treat these variables as alternate measures rather than including both in the MRA; neither is statistically significant when both are included in the MRA.

²⁰ Kaminsky and Schmukler (2008) construct a new database of market liberalization. However, their index does not cover many of the countries in our database. The Economic Freedom of the World index is more comprehensive and available for all the countries in our database.

Economic freedom is a measure of the degree to which market forces are allowed to allocate resources and the degree to which regulations hinder this operation. The series ranges from 1 to 10, with higher values denoting higher levels of economic freedom. This is an aggregate measure of several factors, including legal structure and protection of property rights, freedom to trade and regulation of markets.

Both the market capitalization and the economic freedom series were matched with the countries and time periods used by the primary studies. Table 2 reports the average market capitalization and economic freedom for the samples used by authors for each of the countries included in our data. In light of empirical evidence of Lagoarde-Segot (2009), market capitalization is expected to be inversely related to market inefficiency; the more capitalized is a market the more efficient it should be, *ceteris paribus*. Market capitalization is a measure of equity market development. Underdeveloped stock markets are more likely to contain opportunities for stock market predictability. Underdeveloped markets will contain a larger proportion of small and illiquid stocks, they are more likely to be characterized by thin trading and there is a greater likelihood of market manipulation.

Similarly, the greater the degree of economic freedom (market liberalization), the more efficient should be stock markets. That is, if regulations restrict the operation of markets in terms of their role in price revelation and market clearing function, then restrictions on economic freedom should, *ceteris paribus*, reduce market efficiency. Regulations impose frictions on markets and hence restrict traders from profiting from mispriced assets. Hence, we expect a negative coefficient on the MRA variables, market capitalization and economic freedom.

5. Results

We commence the analysis by calculating basic averages of all *VR1* estimates; these are presented in Table 4. Columns 1 report the simple unadjusted average, while columns 2 and 3 offer weighted averages that have been shown to be less biased when there is selective reporting but as good as conventional meta-analysis when there is no selective reporting (Stanley and Doucouliagos, 2015; Stanley et al., 2017). WLS is an unrestricted WLS weighted average, while WAAP is the WLS weighted average of the only the adequately powered estimates. Note how these are successively smaller than the simple mean, just as one would expect if there were selective reporting. Column 4 reports the FAT-PET (Eq. 3) and column 5 presents the PEESE model results (Eq. 4). As is normally the case when there is publication selection, these weighted averages and the selection bias corrected meta-averages are significantly lower than the simple average, and here they are all of approximately the same magnitude. The t-statistics exceed the higher 3.5 critical value for all averages, be they simple, weighted, or publication bias corrected. All averages suggest a rejection of the EMH for Asian and Australasian stock markets and the FAT (coefficient on standard error) is statistically significant (column 4), suggesting some net positive publication bias in this literature. All of these findings are confirmed in a multiple MRA context after other research and market dimensions are considered. See Table 5 below.

Table 4 about here

WLS estimates of the multiple MRA model, Eqn. (5), are presented in Table 5. We construct these models so that the baseline represents daily returns in Australia and New Zealand.²¹ That is, when all explanatory (or moderator) variables are zero, the constant estimates

²¹ In unreported regressions we used an alternate specification where the baseline of the MRA is high income countries, using the World Bank's classification system; Australia, New Zealand, Singapore, Taiwan, Hong Kong, Japan and South Korea. The results are essentially the same as those reported in the text.

VRI for daily returns in Australasia in 1992 (the sample mean). Column 1 controls for potential publication bias, average year, whether the data is monthly or weekly (with daily as the base), the holding period length used to construct the VR ($HoldingPeriodH = HoldingPeriod - the Australasian mean$) and market capitalization ($MarketCapH = MarketCap - the Australasian mean$). Column 2 adds the dummy variable *LesserIncome*. Column 3 explores further the difference between countries by including fourteen country dummies; it serves as our core MRA model.²²

Columns 4 to 8 explore the robustness of these results to various alternate models.²³ Column 4 uses Robust Regression. Columns 5 and 6 report results from unbalanced panel-data MRA models that include study level effects (see Nelson and Kennedy 2009; Stanley and Doucouliagos 2012). Column 5 reports the results from the fixed-effects panel data WLS model, while column 6 present results from the random-effects panel data WLS model. Both the random and fixed effects panel data models are weighted using inverse variance weights. Column 7 reports results using ‘random effects’ MRA, using modified inverse variance weights, $1/(se_{ij}^2 + \tau^2)$; where τ^2 is the between-study or heterogeneity variance.²⁴ While conventional practice among meta-analysts argues in favor of the random effects model, there is growing concern about this practice, particularly in the presence of publication selection (Stanley and Doucouliagos, 2012 and 2017). Finally, there is no consensus on how clustering should be treated in the very unbalanced data used in MRA. Column 8 reports the results from a multilevel, linear hierarchical model that is one way of handling any data dependence within studies. In

²² Note that we pool all estimates for China. In unreported regressions, we considered separate dummies for Shanghai and Shenzhen indices but these results are not qualitative different to those presented in the text.

²³ We do not report OLS results here as these are not recommended for meta-regression models; OLS treats every observation equally and ignores the fact that precision varies across estimates and studies.

²⁴ The term ‘random effects’ in column 7 refers to the weights used, whereas in column 6 it refers to the normal econometrics usage, as a panel data estimator.

Table 5 we use market capitalization as the key external variable. We also re-estimate these models replacing market capitalization with economic freedom. For the sake of space, only the coefficient on economic freedom is reported in panel B of Table 5 (the full results are available from the authors).

Tables 5 and 6 about here

Most of the results from the MRA models are essentially the same (see Table 5). In particular, the results for *Standard error*, *Average Year*, and *Monthly* are very robust. However, *HoldingPeriodA* is unstable, being statistically significant in some models but not in others and also changing sign in some cases. Although *Weekly* is not robustly greater than the base, daily, all columns of Table 5 estimate the average VR1 to be positive at the weekly frequency—see the bottom of Table 5.

The MRA coefficients can be used to estimate the average VR for different data frequencies. The bottom panel of Table 5 reports these VR1 estimates and tests of the null of the EMH for daily data ($VR1_d$), weekly data ($VR1_w$), and monthly data ($VR1_m$) for the base (Australasia). These are evaluated at sample means. Table 6 reports these tests of the EMH for each country; for each country there is some evidence of violation of the EMH. In general, for daily and weekly data there is evidence of positive autocorrelation (momentum) in Asian and Australasian stock markets. For monthly data the results suggest negative autocorrelation or mean reversion.

Recall that the VR1 is essentially an estimate of the weighted sum of all the autocorrelations up to the k holding period, with the greatest weight placed on lags 1 and 2. Hence, we can interpret it as a correlation coefficient. Our results show that the degree of stock market inefficiency is largest among several of the least developed countries, namely Indonesia, the Philippines and Sri Lanka; with Sri Lanka being the most inefficient. However, market inefficiency is also relatively large in Taiwan. Moreover, some of the estimates suggest that the

absolute value of the VR1 is greater with monthly data. Thus, we can conclude that market inefficiency is larger for the longer data frequency than it is for the shorter data frequency. While these estimates do not directly quantify profits net of transaction costs, they do suggest that the degree of predictability is potentially of economic significance, on average.

6. Discussion

Several important findings emerge from the MRA models.

Standard Error is always statistically significant with a positive coefficient, suggesting publication selection bias. This finding is the opposite of what one would expect from small-sample bias alone. In Appendix A, we show that the variance ratio increases with larger samples size, but our MRA results show that VR1 increases with the standard error. *Ceteris paribus*, the standard error will be inversely related to the sample size. Thus, rather than a preference to support the conventional view, EMH, there appears to be some selective reporting of variance ratios that are greater than one ($VR1 > 0$), relative to those that are less than one. This does not mean that all or even most researchers engage in this practice. It takes only a small minority of negative *VR1* estimates to be suppressed to be detected statistically. Selection bias can inflate the evidence against or in favor of the EMH. Hence, it is important to accommodate or correct this bias. This is what the MRA models in Table 5 achieve; they provide tests for the EMH after allowing for selection bias, enabling more valid inferences to be made.

The coefficient on *Average Year* is negative and is robustly statistically significant, suggesting that the VR ratio falls by about 0.07 per decade. We offer three explanations for this finding. First, it may simply reflect the so-called ‘Prometheus effect’, or the ‘decline effect,’ whereby it has been observed that empirical effects are declining over time (see, for example, Ioannidis 2008). Declining effects are often attributed to initial studies reporting much larger

effects as a result of selection of results that favor novel findings; for example, the earlier studies might have been eager to report a rejection of the EMH. The subsequent literature then finds smaller effects as a broader range of estimates are published. Schwert (2001) speculates that this has indeed occurred in the EMH literature.

A second and arguably more plausible explanation is that this ‘decline effect’ may reflect structural changes that have resulted in less momentum in stock returns and thereby improved stock market efficiency over time. This is consistent with the results from the US stock market (Kim *et al.*, 2011; Ito and Sugiyama, 2009; Gu and Finnerty, 2002). For example, technical advancements in trading systems and platforms, improved transaction flows in stock exchanges, high frequency trading, reduced bid-ask spreads, greater media coverage, increased liquidity, financial products such as exchange-traded funds and greater general awareness of stock markets, can all contribute to increased stock market efficiency. This can also be related with declining level of microstructure factors of emerging stock markets, as Lagoarde-Segot (2009) has found. A third explanation for declining effects was advanced by Schwert (2001) who claims that: “... even if the anomalies existed in the sample period in which they were first identified, the activities of practitioners who implement strategies to take advantage of anomalous behavior can cause the anomalies to disappear (as research findings cause the market to become more efficient).” In essence, Schwert (2001) is arguing that when the market is inefficient in a particular way, the inefficiency is to some degree self-correcting. Once a particular pattern of returns is highlighted and published by researchers, arbitragers can exploit them for profit, which tends to dissolve the pattern in question. Nonetheless, investor irrationality and market inefficiency may persist indefinitely (Shliefer and Summers 1990). A final point worth noting is that the negative sign on *Average Year* indicates that stock market efficiency improves over time. This finding is consistent with Lo’s (2004) adaptive markets hypothesis.

Monthly always has a negative and statistically significant coefficient in the MRA, suggesting that, on average, the use of monthly data results in VR estimates less than one—Tables 5 and 6. Monthly data reveals negative autocorrelation in stock returns for the majority of countries, *i.e.* mean reversion. This means that the variance in stock returns is less than proportional to the investment horizon, whereas market efficiency requires this variance to be proportional. In contrast, on average, the use of daily and weekly data results in positive autocorrelation in stock returns and VR estimates greater than one. The use of monthly observations means that the analysis focuses on patterns that repeat, at most, every two months. We would expect that lagged prices will be less important for explaining future prices the longer is interval at which prices are observed, because serial correlation should decay as the lag length increases.

The two exogenous variables, *MarketCap* and *Ecofreedom* both have the expected negative sign in all specifications except column 2 which adds a dummy variable for lesser income countries. *MarketCap* and *Ecofreedom* are not significant in this specification because these factors tend to have the same effect on market efficiency as economic development. In column 2 of Table 6, it seems that *LesserIncome* captures the effect of all of these forces. Otherwise, the MRA confirms that more developed stock markets, as measured by market capitalization, are also more efficient. Similarly, the MRA confirms that countries with less regulation (more market liberalization) experience greater market efficiency. Our results broadly confirm those of Kaminsky and Schmukler (2008), who find that financial cycles are dampened in the long run by “improvements in property rights, transparency, and overall contractual environment”, all important components of economic freedom.²⁵

²⁵ Kaminsky and Schmukler (2008) find that there is an increase in the short run but in the long run, cycles are less pronounced.

The development level variable, *Lesserinc*, has a positive and statistically significant coefficient, confirming that stock markets are less efficient in the less developed nations. The coefficients on the individual country dummies provide more detailed evidence on the degree to which stock market efficiency varies across countries. In general, stock markets in the less developed countries (*e.g.*, Sri Lanka, Indonesia and the Philippines) are less efficient than those from higher income countries. Kim and Shamsuddin (2008) report similar findings in their investigation of the weak-form efficiency of Asian stock markets using the VR test.

7. Summary and conclusions

The efficiency of markets is one of the cornerstones of finance theory, with profound implications for the functioning of markets and the role of regulators. When markets are efficient, prices reflect fundamental values and hence they allocate scarce funds to their highest valued use. Its prominence in economics and finance notwithstanding, there continues to be considerable debate in the theoretical and empirical literature regarding the EMH. For example, Engel and Morris (1991: 21) conclude that “... the evidence on mean reversion is mixed. Thus, more evidence is needed before declaring the stock market inefficient.” This paper explores the EMH in Asian and Australasian markets. We apply meta-regression analysis to 1,560 estimates of the EMH that use the Variance Ratio test across 16 nations. We intentionally adopt a cross-country comparison, enabling us to analyze stock market efficiency from a relative (comparative) perspective.

Our results indicate that the weight of the evidence from Variance Ratio tests is a rejection of the EMH for Asian nations. Stock market efficiency is particularly weaker in the less developed and more regulated economies. An interesting pattern of results emerges among the different data frequencies. We find small to medium sized inefficiencies among daily and weekly returns and negative autocorrelation among monthly returns. Our results suggest that

there is a degree of inefficiency in Asian stock markets and hence potentially some room for technical analysis and mutual fund managers to outperform the market.²⁶

Market efficiency is often viewed as a final steady state. However, perhaps it is more appropriate to view market efficiency as a process rather than a state. Viewed this way, it is clear from the meta-analysis that stock markets in Asian are becoming more efficient. We find that efficiency has been improving over time and that market capitalization and economic freedom (market linearization) both increase stock market efficiency. These factors mean that it is dubious whether there remain opportunities to outperform the stock market, except in the least developed stock markets and the less liberal nations.

Our focus in this paper has been on Asian stock markets and the Variance Ratio test of the EMH. Meta-analysis could be profitably employed to other regions, especially other emerging economies such as those in the Middle East and Latin America. A particularly important extension would be to apply meta-regression analysis to other tests of the EMH, such as the stock market predictability literature that uses regression analysis.

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²⁶ Recall however that transaction costs and taxation considerations are *not* considered in VR tests.

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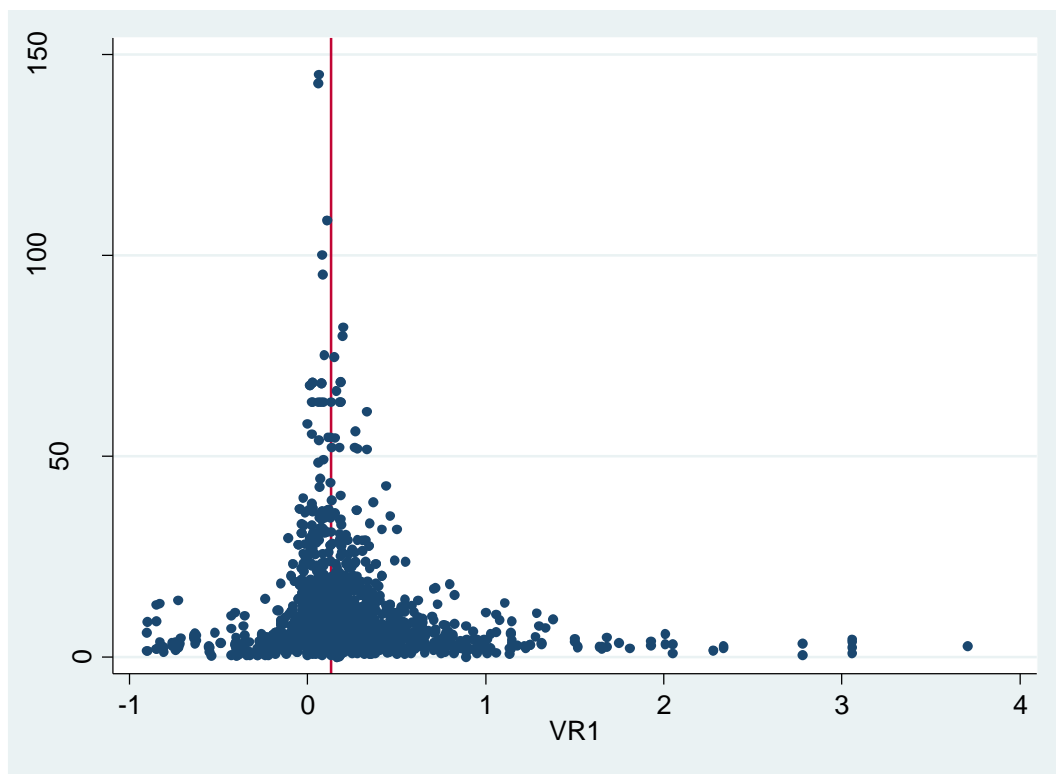
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Figure 1: Funnel Graph, Variance Ratio Estimates



Note: The vertical line illustrates the value of the weighted-average variance-ratio minus one (*VR1*) (0.13), using the inverse variance as weights. Outliers removed.

Table 1: Studies included in the meta-regression analysis

Authors	Countries	Number of estimates	Average VR (range)
Alam, Hasan & Kadapakkam (1999)	Bangladesh, Hong Kong, Malaysia, Sri Lanka, Taiwan	40	1.23 (0.45 - 2.32)

Ayadi & Pyun (1994)	Korea	40	0.96 (0.10 - 4.71)
Chakraborty (2006)	Pakistan	42	1.39 (1.07 - 1.62)
Chang & Ting (2000)	Taiwan	87	1.55 (0.57 - 3.40)
Chen & Jarrett (2011)	China	32	1.25 (1.07 - 1.60)
Cheung & Coutts (2001)	Hong Kong	14	1.07 (0.84 - 1.22)
Claessens, Dasgupta & Glen (1995)	India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Taiwan, Thailand	16	1.24 (0.99 - 1.74)
Cohen (1999)	Japan	12	1.04 (0.90 - 1.23)
Darrat & Zhong (2000)	China	20	1.26 (0.87 - 1.52)
Fuss (2005)	Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand	112	1.61 (0.92 - 4.06)
Groenewold & Ariff (1998)	Australia, Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, Singapore, Taiwan	36	1.79 (0.88 - 3.34)
Guidi & Gupta (2013)	Indonesia, Malaysia, Philippines, Singapore, Thailand	40	1.15 (0.98 - 1.38)
Hassan & Chowdhury (2008)	Bangladesh	4	1.34 (1.26 - 1.40)
Hiremath & Kamaiah (2010)	India	8	1.06 (1.04 - 1.09)
Huang (1995)	Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Thailand, Taiwan	105	1.27 (0.6 - 2.81)
Hung (2009)	China	48	1.15 (0.97 - 1.68)
Islam & Khaled (2005)	Bangladesh	18	1.30 (0.99 - 1.92)
Karemera, Ojah & Cole (1999)	Hong Kong, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand	128	0.98 (0.17 - 2.13)
Kawakatsu & Morey (1999)	India, Korea, Thailand, Malaysia, Philippines	59	1.44 (0.74 - 9.26)
Lai, Balachandher & Nor (2003)	Malaysia	56	1.36 (1.09 - 1.89)
Lee (1992)	Australia, Japan	32	1.23 (0.98 - 1.77)
Lee, Chen & Rui (2001)	China	16	1.21 (1.06 - 1.47)
Lock (2007)	Taiwan	16	1.25 (0.97 - 1.78)
Long, Payne & Feng (1999)	China	4	1.21 (1.10 - 1.30)
Lu & Wang (2007)	China	47	1.06 (0.46 - 2.01)
Rashid (2006)	Pakistan	24	0.85 (0.60 - 1.17)
Patro & Wu (2004)	Australia, Hong Kong, Japan, Singapore,	360	1.12 (0.75 - 1.42)
Youssef & Galloppo (2013)	China, India, Indonesia	46	1.17 (0.91 - 1.39)

Worthington & Higgs (2006)	Australia, China, Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan, Thailand	120	1.18 (0.17 – 2.06)
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Table 2: Individual Country Estimates, Variance Ratio Tests

Country	Number of studies (estimates)	Average VR1	Average market capitalization	Average economic freedom
Australia	4 (118)	0.096	50.26	7.19
Bangladesh	3 (30)	0.309	2.54	5.21
China	6 (168)	0.176	23.84	5.56
Hong Kong	8 (191)	0.029	116.74	8.52
India	6 (60)	0.203	34.87	5.81
Indonesia	8 (84)	0.585	16.35	6.27
Japan	6 (136)	0.085	82.98	7.11
Korea	8 (105)	0.131	44.67	6.13
Malaysia	10 (138)	0.272	160.65	6.99
New Zealand	2 (12)	0.732	38.64	7.63
Pakistan	4 (76)	0.203	15.73	5.58
Philippines	7 (74)	0.419	36.62	6.04
Singapore	6 (139)	0.170	133.53	8.01
Sri Lanka	2 (16)	0.794	14.10	5.61
Taiwan	9 (166)	0.351	65.62	6.95
Thailand	7 (76)	0.378	44.34	6.68

Notes: Average VR1 calculated by the authors from the included studies. $VR1 = VR - 1$.

Table 3: Multiple MRA variables, descriptions and mean and standard deviation

Variable	Description	Mean (standard deviation)
<i>VR1</i>	Variance-ratio, the dependent variable	0.224 (0.42)
<i>Standard error</i>	Standard error of the VR1	0.243 (0.51)
<i>Average year</i>	Mean year of the data used normalized to 1992	0.000 (6.28)
<i>Weekly</i>	Data frequency is weekly (daily is the base). Binary variable.	0.331 (0.47)
<i>Monthly</i>	Data frequency is monthly (daily is the base). Binary variable.	0.280 (0.45)
<i> Holdingperiod</i>	The length of the holding period.	18.098 (59.11)
<i> HoldingperiodA</i>	The length of the holding period minus the mean for Australasia, 29.850	2.030 (59.11)
<i>Marketcap</i>	Average degree of market capitalization	74.864 (59.49)
<i>MarketcapA</i>	Average degree of market capitalization minus the mean for Australasia, 48.12	25.692 (59.49)
<i>EcoFreedom</i>	Average economic freedom	6.783 (0.96)
<i>EcoFreedomA</i>	Average economic freedom minus the mean for Australasia, 7.236	-0.444 (0.96)
<i>LesserIncome</i>	Binary variable for middle and low income countries	0.477 (0.50)
<i>China</i>	Dummy variable with a value of 1 if the data relate to China.	0.122 (0.33)
<i>Korea</i>	Dummy variable with a value of 1 if the data relate to Korea.	0.064 (0.19)
<i>Hong Kong</i>	Dummy variable with a value of 1 if the data relate to Hong Kong.	0.098 (0.30)
<i>India</i>	Dummy variable with a value of 1 if the data relate to India.	0.040 (0.19)
<i>Indonesia</i>	Dummy variable with a value of 1 if the data relate to Indonesia.	0.054 (0.23)
<i>Japan</i>	Dummy variable with a value of 1 if the data relate to Japan.	0.085 (0.28)
<i>Malaysia</i>	Dummy variable with a value of 1 if the data relate to Malaysia.	0.088 (0.28)
<i>Philippines</i>	Dummy variable with a value of 1 if the data relate to Philippines.	0.048 (0.21)
<i>Singapore</i>	Dummy variable with a value of 1 if the data relate to Singapore.	0.092 (0.29)
<i>Taiwan</i>	Dummy variable with a value of 1 if the data relate to Taiwan.	0.102 (0.30)
<i>Thailand</i>	Dummy variable with a value of 1 if the data relate to Thailand.	0.048 (0.21)
<i>Australasia</i>	Dummy variable with a value of 1 if the data relate to Australia or New Zealand.	0.081 (0.27)

Table 4. Average and Meta-Average Variance Ratio and Publication Selection Bias Tests
(Dependent variable is the *VR1*)

	Simple average (1)	Weighted Averages		Publication bias corrected	
		WLS (2)	WAAP (3)	FAT-PET (3)	PEESE (4)
Average VR1	0.224* (21.22)	0.130* (33.98)	0.115* (16.11)	0.102* (20.84)	0.129* (33.60)
Standard error	-	-	-	0.761* (8.99)	-
Standard error squared	-	-	-	-	0.300* (2.54)
Adjusted R ²	-	-	-	0.049	0.01

Notes: The dependent variable in all columns is the variance-ratio minus 1, *VR1*. The number of observations is 1,560. Column 1 reports the simple (unweighted) average variance-ratio. Column 2 reports the unrestricted WLS weighted average variance-ratio minus 1, with the inverse variance as weights (Stanley and Doucouliagos, 2015). Column 3 calculates the WAAP, which is the WLS weighted average on only those estimates that have adequate power (>80%) (Stanley et al., 2017). Column 4 displays the results from the FAT-PET model (Eq. 3), while column 5 reports the results from the PEESE model (Eq. 4). Columns 4 and 5 are estimated using weighted least squares (WLS), with the inverse variance as weights. Parentheses report t-statistics. * denotes statistical significance at least at the 5 percent level. We raise the critical value for the PET coefficient to 3.5 to allow for small-sample bias, but here it is nearly 6 times larger than 3.5 (see Appendix A).

Table 5. Multiple Meta-Regression Results
(Dependent variable is the *VR1*)

Variables	WLS (1)	WLS (2)	WLS (3)	Robust (4)	FE Panel (5)	RE Panel (6)	Random effects (7)	Multi- level (8)
<i>Constant</i>	0.108* (8.70)	0.054* (4.27)	0.046* (4.16)	0.093* (11.38)	0.017 (1.42)	0.018 (1.54)	0.098* (4.36)	0.016 (1.41)
<i>Standard error</i>	1.024* (9.21)	1.079* (9.13)	1.106* (11.65)	0.599* (9.87)	1.416* (17.12)	1.402* (7.10)	0.342* (4.54)	1.563* (4.17)
<i>Average year</i>	-0.003* (-3.03)	-0.006* (-5.47)	-0.007* (-6.39)	-0.007* (-12.71)	-0.007* (-6.76)	-0.007* (-7.34)	-0.012* (-7.66)	-0.007* (-7.07)
<i>Monthly</i>	-0.168* (-10.86)	-0.172* (-10.67)	-0.191* (-12.03)	-0.163* (-14.16)	-0.143* (-8.46)	-0.152* (-8.95)	-0.204* (-10.18)	-0.146* (-8.71)
<i>Weekly</i>	0.028 (1.45)	0.033* (1.70)	-0.006 (-0.39)	-0.009 (-1.15)	0.022* (1.92)	0.010 (0.89)	0.028 (1.61)	0.017 (1.58)
<i> HoldingPeriodA</i>	-0.000 (-0.31)	-0.000 (-0.97)	-0.000 (-1.30)	0.002* (10.43)	-0.001* (-4.18)	-0.001* (-4.33)	0.001* (5.31)	-0.001* (-4.38)
<i> MarketCapA</i>	-0.0004* (-4.18)	-0.0001 (-1.11)	-0.002* (-4.60)	-0.001* (-6.16)	-0.001* (-5.69)	-0.002* (-6.28)	-0.002* (-4.08)	-0.001* (-5.97)
<i> LesserIncome</i>	-	0.085* (5.85)	-	-	-	-	-	-
<i> Bangladesh</i>	-	-	-0.062* (-2.61)	-0.024 (-0.72)	-0.022 (-0.45)	-0.037 (-0.76)	0.087 (1.23)	-0.027 (-0.56)
<i> China</i>	-	-	0.025 (1.00)	0.069* (5.94)	-0.051* (-2.62)	0.004 (0.20)	0.119* (3.35)	-0.030 (-1.58)
<i> India</i>	-	-	0.086* (5.05)	0.088* (5.63)	0.082* (3.47)	0.088* (3.84)	0.125* (3.03)	0.085* (3.65)
<i> Indonesia</i>	-	-	0.110* (4.01)	0.125* (7.66)	0.113* (5.21)	0.116* (5.23)	0.274* (6.63)	0.114* (5.29)
<i> Malaysia</i>	-	-	0.288* (6.84)	0.243* (11.01)	0.248* (8.20)	0.268* (8.78)	0.328* (6.42)	0.255* (8.51)
<i> Philippines</i>	-	-	0.155* (8.55)	0.160* (10.54)	0.157* (7.90)	0.161* (7.93)	0.242* (6.08)	0.158* (8.03)
<i> Sri Lanka</i>	-	-	0.275* (3.87)	0.540* (22.10)	0.273* (8.47)	0.273* (8.33)	0.576* (8.58)	0.273* (8.53)
<i> Thailand</i>	-	-	0.116* (5.09)	0.121* (7.51)	0.112* (5.30)	0.116* (5.39)	0.183* (4.76)	0.114* (5.41)
<i> Pakistan</i>	-	-	0.027 (0.99)	0.073*** (4.30)	-0.023 (-0.84)	-0.016 (-0.61)	0.151*** (3.55)	-0.021 (-0.79)
<i> Korea</i>	-	-	-0.046 (-1.31)	-0.003 (-0.21)	-0.007 (-0.34)	-0.010 (-0.46)	-0.066* (-1.86)	-0.008 (-0.36)
<i> Hongkong</i>	-	-	0.200* (3.89)	0.121* (4.49)	0.176* (4.65)	0.195* (5.16)	0.173* (2.94)	0.183* (4.90)
<i> Japan</i>	-	-	-0.043* (-2.48)	-0.060* (-4.91)	-0.047* (-2.95)	-0.043* (-2.67)	-0.029 (-0.94)	-0.046* (-2.87)
<i> Singapore</i>	-	-	0.242* (6.88)	0.181* (9.63)	0.220* (8.51)	0.235* (9.04)	0.198* (4.59)	0.226* (8.81)
<i> Taiwan</i>	-	-	0.200* (5.86)	0.158* (12.00)	0.162* (8.38)	0.170* (8.76)	0.249* (7.79)	0.164* (8.61)
<i> VR1_d</i>	0.108* (8.70)	0.054* (4.27)	0.046* (4.16)	0.094* (11.38)	0.017 (1.42)	0.018 (1.54)	0.098* (4.36)	0.016 (1.41)
<i> VR1_w</i>	0.136* (6.51)	0.087* (3.95)	0.040* (2.30)	0.084* (7.47)	0.038* (2.37)	0.028* (1.74)	0.125* (4.92)	0.034* (2.13)
<i> VR1_m</i>	-0.060* (-3.18)	-0.117* (-5.75)	-0.145* (-7.22)	-0.070* (-4.86)	-0.126* (-6.10)	-0.134* (-6.41)	-0.106* (-3.81)	-0.129* (-6.30)
<i> Adjusted R²</i>	0.139	0.178	0.359		0.371	0.354	0.510	
<i> B: EcofreedomA</i>	-0.025* (-3.90)	0.004 (0.45)	-0.069* (-3.02)	-0.092* (-8.25)	-0.039* (-2.06)	-0.066* (-3.61)	-0.081* (-2.51)	-0.053* (-2.86)

Notes: The dependent variable in all columns is the variance-ratio minus 1. The number of observations is 1,554. Cell entries in parentheses report t-statistics. All estimates use weighted least squares (WLS), with the inverse variance as weights and using robust

standard errors for columns (1)-(3). Columns (4)-(6) test the robustness of the basic WLS findings using robust regression (4), fixed-effects panel methods (5), random-effects panel (6), random effects weights (7), and multi-level (8) methods. $VR1_d$, $VR1_w$, and $VR1_m$ denote the estimated Variance Ratio using daily, weekly and monthly data for the base (Australasia), respectively, evaluated at sample means; figures in brackets are t-statistics testing $VR1 = 0$. *denotes statistically significant at least at the 5% level, one-tail test. R^2 in columns (4) and (5) are for variations among the reported t-values in this research literature. Panel B reports the coefficient on economic freedom, replacing this with market capitalization. This model uses the same specification but for the sake of brevity the coefficients on the other variables are not reported.

Table 6. Country Specific MRA tests of the EMH, Daily, Weekly and Monthly Data

Country	Daily data	Weekly data	Monthly data
	$VR1_d$ (1)	$VR1_w$ (2)	$VR1_m$ (3)
<i>Bangladesh</i>	0.060* (4.49)	0.054* (2.74)	-0.131* (-6.21)
<i>China</i>	0.104* (5.10)	0.099* (4.28)	-0.086* (-3.36)
<i>Korea</i>	0.002 (0.07)	-0.003 (-0.09)	-0.188* (-5.19)
<i>Hong Kong</i>	0.029* (2.30)	0.023 (1.22)	-0.162* (-7.42)
<i>India</i>	0.152* (10.87)	0.146* (7.88)	-0.039* (-1.89)
<i>Indonesia</i>	0.211* (9.66)	0.205* (7.36)	0.020 (0.75)
<i>Japan</i>	-0.053* (-4.86)	-0.058* (-3.38)	-0.243* (-11.49)
<i>Malaysia</i>	0.156* (7.94)	0.151* (6.60)	-0.035 (-1.48)
<i>Philippines</i>	0.220* (15.00)	0.215* (10.80)	0.030 (1.39)
<i>Sri Lanka</i>	0.377* (5.44)	0.371* (5.24)	0.186* (2.64)
<i>Singapore</i>	0.152* (14.38)	0.147* (8.33)	-0.038* (-1.97)
<i>Taiwan</i>	0.224* (6.47)	0.219* (6.64)	0.034 (0.90)
<i>Thailand</i>	0.173* (7.99)	0.167* (6.47)	-0.018 (-0.66)
<i>Australasia</i>	0.046* (4.16)	0.040* (2.30)	-0.145* (-7.22)

Notes: The cells report estimates using the MRA coefficients from Table 5, column 3, evaluated at the mean of the samples for average year and market capitalization. Figures in brackets are t-statistics. $VR1_d$, $VR1_w$, and $VR1_m$ denote the estimated Variance Ratio using daily, weekly and monthly data, respectively. * denotes statistically significant at least at the 5% level, one-tail test.