Predictability in securities price formation: differences between developed and emerging markets

Silvio John Camilleri and Semiramis Vassallo

Department of Banking and Finance, FEMA, University of Malta, Msida, Malta, and

Ye Bai

International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, China

Abstract

Purpose – This paper examines whether there are differences in the nature of the price discovery process across established versus emerging stock markets using a twenty-country sample.

Design/methodology/approach – The authors analyse security returns for traces of predictability or non-randomness using variance ratio tests, Granger-Causality models and runs tests.

Findings – The findings pinpoint at predictabilities which seem inconsistent with market efficiency, and they suggest that the inherent cause of predictability differs across groups.

Research limitations/implications – The authors present empirical evidence which may be used to attain a deeper understanding of the links between predictability and market efficiency, in view of the conflicting evidence in prior literature.

Practical implications – Whilst the pricing process in emerging markets may be hindered by delayed adjustments, in case of established markets it seems that there is a higher tendency for price reversals which could be due to prior over-reactions.

Originality/value – This study presents evidence of substantial differences in predictability across developed and emerging markets which was gleaned through the rigorous application of different empirical tests.

Keywords Delayed price adjustments, Emerging markets, Granger-causality, Liquidity, Over-reactions, Predictability, Price discovery, Runs tests, Variance ratio tests, Vector autoregression

Paper type Research paper

1. Introduction

One fundamental idea in the finance discipline is the concept of market efficiency whereby stock returns are expected to fluctuate unpredictably as any news and additional elements which may be forecasted are promptly priced in. Return predictability in securities markets is important both due to its connotations to profitable trading opportunities (Kaniel *et al.*, 2008) and for its implications *vis-à-vis* market efficiency (Poterba and Summers, 1988), yet past literature yielded conflicting insights regarding the presence or degree of predictability across markets. In practice, stock market data often feature predictability patterns, which may emanate from over- or under-reaction to news (Piccoli *et al.*, 2017; Al-Thaqeb, 2018), and market microstructure factors such as non-synchronous trading (Camilleri and Green, 2014),

the bid-ask spread bounce (Kandel *et al.*, 2012), the execution of stale limit orders (Berkman, 1996), and the splitting of large orders into smaller ones (Lee *et al.*, 2004).

The former array of predictability sources coupled with inconsistent empirical findings imply that the interpretation of observed patterns and their coexistence with vigilant traders promptly reacting to new information are still unresolved areas. In view of the fact that the long-established approaches of checking for predictability to infer whether markets are behaving in an efficient manner have not really resulted in clear-cut insights, in this paper we aim to delve deeper into the possible differences in predictability across markets – if such variations do exist it is of fundamental importance that they are investigated since they may prove vital in coherently designing further studies relating to this topic.

This comparative study is intended to offer a contribution to the literature relating to predictability on various accounts: (1) we undertake a cross-sectional comparison between emerging and developed markets to analyse whether the nature of the predictability differs across these groups, (2) we extend the existing empirical evidence to encompass data which reflects more recent developments which significantly impacted on financial markets, and (3) we present empirical evidence which may be used to attain a more thorough interpretation of current perspectives regarding the links between predictability and market efficiency.

Given that emerging securities markets are usually less liquid, more volatile and feature higher predictability (Bekaert and Harvey, 1997), one may expect that these would be less efficient than established ones and in that case the price formation process is likely to differ in between these groups. Yet, such hypothesised variations should not be taken for granted in view of the fact that emerging markets registered substantial progress in terms of their openness to foreign investors and information disclosure requirements. One may also deduce that the differences in terms of securities trading technology are not so pronounced and consistent technological upgrades may in turn foster more vigorous markets (Yılmaz *et al.*, 2015). Research has also pointed at the integration of emerging markets with their established counterparts (Camilleri and Galea, 2009; Mohti *et al.*, 2019; Al-Nasser and Hajilee, 2016). In view of this, it is important to extend the empirical evidence to attain a clearer idea as to how the formation of prices may differ across markets. In particular, we assess the return predictability of ten established markets (Australia, Canada, France, Germany, Hong Kong, Israel, Japan, Sweden, UK and the US) and ten emerging ones (Brazil, Chile, China, Greece, India, Malaysia, Mexico, Poland, Russia and South Africa) for the period January 2004–December 2018 [1].

In view of the fact that different tests relating to predictability and pricing efficiency may yield incongruent insights (Worthington and Higgs, 2006), we adopt more than one approach. We first conduct variance ratio (VR) tests in order to assess whether stock returns follow a random walk. Then we apply Granger-Causality modelling to investigate specific serial dependencies in stock index data. Such dependencies include the relationship of the fluctuations of a country index with its own lags, as well as the trading days required for a country index to adjust to overseas developments as approximated by a global stock index. The randomness or otherwise of stock market returns is also assessed through runs tests which consider whether fluctuations change direction as frequently as one would expect in a randomly generated series. The combination of parametric and non-parametric approaches in our methodology implies that we do not over-rely on the assumption of normally distributed data and we believe that this is one of the inherent strengths of this study [2].

An additional worth of our investigation is that, although numerous authors have focused on return predictability in developed markets and to a lesser extent on emerging ones, direct comparisons between the respective groups were much less prevalent. Among the select prior studies which compared the return predictability in these market groups, Srivastava (2007) focused on six Asian emerging markets and six developed markets. We refine on the former study since we do not restrict the selected emerging markets to the Asian region, and we also

use a larger sample of countries. In addition, our selection of geographically dispersed markets offers the potential to consider whether data predictability could be the result of time-zone differences, which may be difficult to deduce when the sampled countries fall in similar time-zones.

A different study which is closer to ours is Griffin *et al.* (2010) which investigated the predictability across developed and emerging markets with the objective of assessing the differences in market efficiency in between these groups. The authors did not find evidence that trading on the basis of predictability yields significantly different returns across these markets. The sample period used by Griffin *et al.* (2010) ends in 2005; since then noteworthy events took place which one may deduce to have impacted on the degree of integration and predictability across markets. These include the 2007/08 financial crisis, the UK's reconsideration of its EU membership, and various policies on part of different emerging markets seeking further liberalisation. Overall, the expected benefits of globalisation are being increasingly debated, with some countries such as the US no longer being at the forefront to promote this concept. In view of this, our analysis furthers the existing empirical evidence by using more recent data spanning from 2004 to 2018 to incorporate such trends.

This paper is organised as follows. Section 2 summarises the relevant literature while section 3 describes the methodology. Section 4 offers details about the data set and the empirical results are shown in the subsequent section. Section 6 concludes.

2. Literature review

Numerous studies have tested for predictability in securities prices and the empirical results yielded contrasting insights which vary across markets, sample periods, and research approaches. We believe that in order to better understand this important issue, literature stands to gain through inquiries into the nature of predictability, in view of the fact that the conventional approaches of applying predictability tests to make inferences about market efficiency left the debate unresolved. We thus opt to search for differences in the nature of predictability across developed and emerging markets, on the grounds that it is well documented that these groups feature distinct characteristics (e.g. Bekaert and Harvey, 1997; Hung, 2009). For instance, emerging markets tend to have lower liquidity, higher commonality in liquidity, higher volatility, and a tendency for low correlation with developed market returns. This may be expected to materialise in a higher level of predictability in emerging markets, owing to lower informational efficiency due to the typically lower liquidity levels and higher information costs (Griffin *et al.*, 2010). Nonetheless, in view of the fact that emerging markets have become more integrated with established ones over the years (Mohti *et al.*, 2019), it is important to understand whether such differences have indeed persisted. An awareness of these factors is of pertinence to academics on the grounds that this may lead to a much needed insight in order to reconcile conflicting evidence, as well as fund managers who may want to infer whether trading strategies which proved successful in one market group may be relevant to the other.

2.1 Predictability in developed markets
Past literature yielded inconsistent insights regarding the presence and the degree of predictability in stock market data. Studies which focus on developed markets include Narayan and Smyth (2007) who used data of fifteen industrial European stock markets from 1960 to 2003 and found evidence which supports the random walk process. Conversely, when applying runs tests and VR tests to the S&P 500 Index for the period 2008–2018, Pernagallo and Torrisi (2020) found varying degrees of predictability for several stocks.

Worthington and Higgs (2006) checked for random walk patterns in daily stock data for Australia, Hong Kong, Japan, New Zealand and Singapore. The presence of serial correlation suggested that markets do not follow a random walk, however unit root tests indicated otherwise. VR tests indicated that only Hong Kong and New Zealand fulfilled the most rigorous random walk requirements. Borges (2010) investigated the informational efficiency of the French, German, Portuguese, Spanish and UK markets during the period 1993–2007, through VR tests and runs tests. Weak form efficiency was rejected for Portugal, France and UK, but not in case of Germany and Spain. Boya (2019) used VR tests and reported that the French stock market during the period 1988–2018 exhibited varying degrees of serial dependencies at different points in time; such inefficiencies are more prone to occur during major macroeconomic events.

2.2 Predictability in emerging markets
A strand of studies considered the price behaviour in emerging markets and reported varying degrees of predictability. Alexakis et al. (2010) investigated the predictability of the Athens Stock Exchange between 1993 and 2006 and found that financial ratios convey valuable information in predicting the cross-section of stock returns. Nisar and Hanif (2011) applied runs tests, serial correlation tests, unit root tests and VR tests on data from the stock exchanges of Karachi, Bombay, Colombo, and Dhaka. The authors reported that none of these markets follows a random walk.

Other studies focusing on emerging markets yielded mixed insights. Abrosimova et al. (2002) investigated the predictability of the Russian stock market for the period 1995–2001. Applying various tests such as VR, the authors found significant evidence of predictability in daily and weekly data but less so in the case of monthly data. Worthington and Higgs (2006) analysed the stock markets of China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan and Thailand. The presence of random walks in daily returns was rejected through serial correlation and multiple VR procedures, yet unit root tests suggested that data exhibited the required characteristics of a random walk.

2.3 Predictability and market efficiency
Elements of predictability such as price reversals go against the notion of an efficient market, since in the latter framework profit maximising traders set market prices which reflect all available information including any elements which may be forecasted. Nonetheless, delayed reactions to economic and other pertinent information, may still induce predictability in stock prices. For instance, studies such as Dhakal et al. (1993) and Camilleri et al. (2019) suggest that the interaction between interest rates and money supply is a leading indicator of stock prices across different developed economies.

Although the absence of predictability in a random walk is conventionally considered as a sufficient condition for market efficiency, the rejection of a random walk does not necessarily imply stock market inefficiency. For instance, limited market liquidity plays an important role, in that traces of predictability may be the result of non-synchronous trading (Camilleri and Green, 2014) or large orders being split into smaller components for gradual execution (Lee et al., 2004). Further market microstructure elements which may cause predictability in stock prices include the bid-ask spread bounce which induces negative serial correlation in security prices (Kandel et al., 2012) and the execution of stale limit orders (Berkman, 1996).

Conversely, more recent studies question the idea that a random walk should be automatically considered as "evidence" of an efficient market. Griffin et al. (2010) hypothesise an extreme case of a security where the price never responds to news and changes constitute solely of noise. If the latter is a totally random component, the price series will still feature no predictability – despite the fact that it is inefficient.

Seminal studies such as Campbell *et al.* (1997) and Lo and MacKinlay (1999) argue that perfect efficiency is just an idealisation which is impossible to achieve in practice. A strand of literature considers how occasional irrational behaviour may be due to limited information and resources entailed to analyse vast data. As per the adaptive market hypothesis (AMH), participants with limited access to information revise their expectations and adapt to an evolving uncertain environment (Daniel and Titman, 1999; Lo, 2004). Hence decisions may at times deviate from optimal ones (Lo, 2004).

At the macro level, economic reforms, financial regulations, and improved technology can also cause market efficiency (and therefore predictability) to change over time (Fifield and Jetty, 2008; Freund and Pagano, 2000; Gu and Finnerty, 2002; Lu *et al.*, 2007; Vo, 2017).

2.4 Emerging markets as compared to developed ones
Overall, earlier studies yielded contrasting results with respect to the degree of predictability of securities markets and further insights are needed to resolve the ensuing debate. It is therefore one main intention of this paper to look for any differences in the nature of predictability across emerging and established markets, since the awareness of such differences would be of seminal importance in coherently designing further studies relating to this topic.

In addition, we may note that most studies which tackled multiple markets have focused on neighbouring groups, whereas investigations which tackle the differing predictability across developed and emerging markets are far less prevalent. Research by Srivastava (2007) compared the pricing efficiency of six emerging Asian markets with six developed markets through serial correlations, runs tests, and mean square of successive difference tests. The author found no significant differences in predictability. As outlined earlier, our approach refines on this study by using a larger sample where emerging markets are not limited to the Asian region. This also offers the potential to inquire whether data predictability could be the result of time-zone differences, which may not be possible to analyse clearly when using a sample of proximate countries.

Griffin *et al.* (2010) analysed a wider sample of countries by applying various tests such as VR and delay measures and found that there was a higher tendency for developed markets to deviate from the random walk, as compared to emerging ones. Yet the authors also noted that if there is lower information production in emerging markets, conventional approaches to measuring efficiency are biased towards indicating that emerging markets are less predictable and more efficient.

In view of this, inquiring about the inherent nature of predictability across these market groups is fundamental in attempting to assimilate the conundrum of conflicting evidence, and it is the aim of this study to offer a contribution in this scantily researched area. Stated more formally, we would like to test the hypothesis of no difference in predictability between developed and emerging markets owing to market integration, against the alternative hypothesis that predictability varies across these groups since there are still material underlying disparities between them.

3. Methodology
In investigating whether the price formation process in the sampled markets features any predictability, we start by conducting variance ratio (VR) tests. A basic VR test (Lo and MacKinlay, 1988) examines the predictability of time series data by comparing variances of returns calculated over different time intervals. This is based on the notion that if returns follow a random walk or a martingale, the variance of random walk increments is linear in all intervals, i.e. the variance of x-period difference should be x times the variance of one-period

difference. We choose two, three, four and five multiple lengths for daily data and two, four, six and eight for the five-trading day interval data. Lo and MacKinlay (1988) proposed two test statistics for the random walk properties: homoskedasticity-robust VR estimators and the heteroskedasticity-robust VR estimators assuming a martingale difference sequence. However, Lo and MacKinlay (1989) noted that basic VR tests suffer from two major limitations: first, they are asymptotic tests with their sampling distributions approximated on the basis of their limiting distributions [3]. Wright (2000) suggested a nonparametric alternative using rank- and sign-based tests, which outperform the conventional VR tests. In addition, the author showed that rank-based tests have the advantage of low size distortion under conditional heteroskedasticity.

The second limitation of the basic VR tests as proposed by Lo and MacKinlay (1988) and Wright (2000) is a higher risk of type 1 error since the test statistic is not adjusted for the multiple comparisons involved in the process. Therefore, it could result in the over rejection of a null hypothesis when this is in fact true (Richardson, 1993). Several improved versions of the basic VR test were therefore proposed. Chow and Denning (1993) developed a test statistic that examines the maximum absolute value of a set of multiple VR statistics, which improves on the basic VR test by using the studentized maximum modulus distribution when computing the critical values. A more recent refinement to overcome the asymptotic distribution is a wild bootstrap approach developed by Kim (2006). This resampling approach first computes joint (Chow and Denning, 1993) Wald VR test statistics on *t*-observation samples generated by weighting the original data by random variables, and then applies the wild bootstrap which approximates the sampling distribution of the VR test statistic. When the sample becomes larger, type 1 errors tends to be less prevalent for bootstrapping tests than for asymptotic tests (Mackinnon, 2002). Since the sampling distribution is an approximation, the wild bootstrap can accommodate data with unknown forms of conditional and unconditional heteroskedasticity (Davidson and Flachaire, 2008; Mackinnon, 2002). Given the size of the sample used in this study, we also apply the wild bootstrap to evaluate the statistical significance of Chow-Denning joint tests with unbiased *p*-values.

Following the VR tests, we proceed with modelling lead-lag effects through VAR estimations. If shocks in one variable lead to fluctuations in a different variable, then the former "Granger-causes" the latter (Granger, 1969). A bivariate VAR may be used to model two variables as autoregressive processes, with the added lags of the other variable and a residual term, as follows:

$$x_t = \sum_{i=1}^{n} \alpha_{1i} x_{t-i} + \sum_{i=1}^{n} \beta_{1i} y_{t-i} + u_{1t} \tag{1}$$

$$y_t = \sum_{i=1}^{n} \alpha_{2i} x_{t-i} + \sum_{i=1}^{n} \beta_{2i} y_{t-i} + u_{2t} \tag{2}$$

where x_t and y_t are the variable observations at time t, n is the number of observations, and u_t is a residual term.

We use the above specification to examine whether any predictability exists in between the stock indices of various countries and a global stock index. Such serial dependencies may emanate from pricing inefficiencies, delayed adjustments due to non-synchronous trading (Camilleri and Green, 2014), and due to time-zone differentials. Further serial dependencies in the data may arise from the bid-ask spread bounce (Kandel *et al.*, 2012), and the practice of splitting large trading orders into smaller ones (Lee *et al.*, 2004), although these may be expected to be less pronounced in index data as opposed to individual stock data. On the

grounds that the effects of such transient factors may not be as robust in lower frequency data, we also estimate VAR models using data which were sampled at longer intervals to compare the results with the first round of estimations.

As our third approach at looking for serial dependencies in the price formation process, we use the Wald-Wolfowitz Runs Tests for stochasticity, where a run is defined as a series of innovations featuring a common occurrence. If prices fluctuate unpredictably, it is unlikely that returns fluctuate successively in the same direction over an extended period. In this case the two possible runs are a series of continuous fluctuations which are greater than the mean return (an up run of positive innovations) and a series of uninterrupted fluctuations which are lower than the mean return (a down run of negative innovations). Runs tests compare the expected number of runs in a random process with the actual number of runs in a time-series to check for any serial dependencies.

Under the null hypothesis, the number of runs in a time series is a random variable with the following moments:

$$\mu_R = \frac{2N_1 N_2}{N_1 + N_2} + 1 \tag{3}$$

$$\sigma_R^2 = \frac{2N_1 N_2 (2N_1 N_2 - N_1 - N_2)}{(N_1 + N_2)^2 (N_1 + N_2 - 1)} \tag{4}$$

where μ_R is the mean (expected number of runs), N_1 and N_2 refer to the number of positive and negative innovations in a time series respectively, and σ_R^2 is the variance of the number of runs. The test statistic Z tends towards a normal distribution in case of sufficiently large samples, and is defined as follows:

$$Z = \frac{R - \mu_R}{\sigma_R} \approx N(0, 1) \tag{5}$$

where R is the total number of runs. When the difference between the actual number of runs and the expected number of runs is statistically significant, the null hypothesis of random fluctuations is rejected. Both a relatively large and a relatively low number of runs are indicative of serial dependencies. The lower the number of runs, the higher the possibility of positive serial dependencies which may emanate from delayed reaction to news, or liquidity-oriented factors such as non-synchronous trading. Conversely, an excessively high number of runs may suggest a tendency for the reversal of returns (possibly due to prior overreactions) or liquidity-related fluctuations such as the reversal of the price impact of block transactions.

Given that runs tests only consider the direction of a change rather than magnitude, they adopt a non-parametric approach. This offers the advantage that they do not pre-suppose normally distributed data when this is not usually the case in finance (Camilleri, 2006; Escha, 2010).

The tests we conduct are often used to make inferences about the efficiency of the underlying markets. Nonetheless, we would caution against the interpretation of the empirical insights as a comparison of the respective efficiency across market groups, since a coherent approach in this respect would entail factoring in the differences in the information-generation process between the groups (Griffin et al., 2010). Rather, our aim is to investigate whether the nature of any predictability differs across developed and emerging markets.

4. Data
The data used in this study comprises daily equity indices for ten established markets and ten emerging ones as shown in Table 1. In distinguishing between market groups, we adopted the Morgan Stanley Capital International (MSCI) classifications at the date of sampling. We opted

to use index values rather than data for individual stocks on the grounds that the former should be less prone to the idiosyncrasies applicable to individual stocks such as the execution of stale limit orders and the typical bid-ask spread bounce. In addition, index data may be more suited for straightforward comparisons between markets since indices are less impacted by company-specific news, and therefore one may expect a more uniform flow of news for such data.

We included countries falling in different time zones in our sample; given that predictability across markets could emanate from the fact that markets may be closed while relevant developments are taking place overseas. The fact that our sample includes a selection of geographically dispersed markets offers the potential to consider whether any data predictabilities could be the result of such time-zone differences as opposed to a delayed-reaction of traders. In addition, the markets comprising the sample feature comprehensive diversity in terms of their market capitalisation as shown in Table 1.

As a yardstick of global equity markets performance, we used the Morgan Stanley Capital International - All World Country Index (ACWI) which gauges the performance of 23 established and 26 emerging markets.

The data set comprised the closing prices of these indices over the period 6th January 2004–31st December 2018 and were obtained via Bloomberg. This time span not only offers the potential to augment the current literature with more recent evidence, but it is also less prone to recency bias in view of its considerable longevity.

In parts of this study, we re-sampled the index values at five-day intervals, as detailed in Section 5. In compiling the data set for the individual markets for the purpose of modelling the comovement with ACWI, we omitted those trading days where an observation was

		$ bn	%
Developed markets			
Australia	S&P/ASX 200 (AS51)	1,263	88.1
Canada	S&P/Toronto Stock Exchange Composite Index (SPTX)	1938	113.1
France	Cotation Assistée en Continu 40 (CAC40)	2,366	85.2
Germany	Deutscher Aktien Index (DAX)	1755	44.5
Hong Kong	Hong Kong Sang Index (HSI)	3,819	1,053.0
Israel	Tel Aviv Stock Exchange 125 Index (TA-125)	187	50.6
Japan	Nikkei-225 Stock Average	5,297	106.5
Sweden	OMX Stockholm 30 Index (OMX)	290	87.2
UK	FTSE 100	1868	63.9
US	S&P 500	30,436	148.1
Emerging markets			
Brazil	Ibovespa Brasil São Paulo Stock Exchange Index (IBOV)	917	49.1
Chile	S&P/CLX IPSA (IPSA)	251	84.1
China	Shanghai Stock Exchange Composite Index (SHCOMP)	6,325	46.5
Greece	Athens Stock Exchange General Index (ASE)	38	17.6
India	NSE Nifty 50 Index	2083	76.6
Malaysia	FTSE Bursa Malaysia KLCI Index	398	111.0
Mexico	S&P/BMX IPC (MEXBOL)	385	31.5
Poland	WIG20 Index	160	27.4
Russia	MOEX Russia Index	576	34.8
South Africa	FTSE/JSE Africa All Share Index (JALSH)	865	235.0

Table 1.
Indices of sampled markets and market capitalisations

Note(s): The table shows the sampled countries and the respective indices used in the study. The last two columns report the market capitalisation in US Dollars (billions) and as a percentage of GDP. Capitalisation statistics were obtained from the World Bank Database and reported as at 2018, except for Sweden (as at 2003) and the UK (as at 2008)

missing for one of the respective indices. Following checks for stationarity using Augmented Dickey–Fuller Tests, all indices were transformed to log returns to be used in subsequent modelling.

5. Empirical results
5.1 Variance ratio (VR) tests
The daily return results of Chow–Denning tests of a martingale hypothesis are shown in Table 2. We present Max $|z|$ statistics with probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom. We conducted Chow–Denning joint VR tests, using both homoscedasticity robust test statistics and heteroscedasticity robust test statistics. In Panel A we follow the asymptotic distribution using a critical value of 2.49 while in Panel B we do not rely on the asymptotic distribution by using the confidence intervals calculated with the Wild Bootstrapping method. Uniformly, the test statistics are highly significant, and the null hypothesis of a martingale is rejected across all markets.

Table 3 presents the daily return results of the Joint Rank (MR1), Rank Score (MR2) and Sign (MS) tests. Test probabilities were computed using permutation bootstrap. The results strongly reject the null hypothesis of a random walk (rank and rank score tests) and a martingale (sign test) for all of the markets since all the Max $|z|$ statistics are highly significant. In addition, the results are consistent with those shown in Table 2.

Market	Dof	Homoscedasticity robust test statistics max $|z|$		Heteroscedasticity robust test statistics max $|z|$	
		Panel A	Panel B	Panel A	Panel B
Australia	3,782	30.22	30.22	10.03	10.03
Canada	3,761	28.57	28.57	10.00	10.00
France	3,839	30.85	30.85	14.18	14.18
Germany	3,809	29.99	29.99	15.15	15.15
Hong Kong	3,697	30.93	30.93	11.75	11.75
Israel	3,606	29.44	29.44	15.47	15.47
Japan	3,675	34.00	34.00	17.00	17.00
Sweden	3,766	30.31	30.31	14.52	14.52
UK	3,788	29.86	29.86	13.04	13.04
US	3,771	31.73	31.73	11.39	11.39
Brazil	3,705	28.62	28.62	13.55	13.55
Chile	3,736	26.91	26.91	11.08	11.08
China	3,642	28.84	28.84	16.00	16.00
Greece	3,712	26.85	26.85	13.96	13.96
India	3,704	27.08	27.08	13.57	13.57
Malaysia	3,686	26.76	26.76	12.14	12.14
Mexico	3,758	25.91	25.91	12.39	12.39
Poland	3,732	27.79	27.79	16.84	16.84
Russia	3,723	29.06	29.06	11.01	11.01
South Africa	3,735	28.94	28.94	16.21	16.21

Note(s): 1. This table presents daily return results of Chow–Denning tests (test of Martingale hypothesis). Results for developed markets are shown on the top, whilst those for emerging markets are shown below
2. The presented statistics are Max $|z|$ with probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom
3. All the test statistics are statistically significant (different from 1), using a critical value of 2.49 (panel A) and using the confidence intervals calculated with the Wild Bootstrapping method (panel B). The results strongly reject the null hypothesis of a martingale across all markets

Table 2.
Chow–Denning joint variance ratio test results based on daily returns

The table has columns: Market, Dof, MR1 max |z|, MR2 max |z|, MS max |z|.

Market	Dof	MR1 max |z|	MR2 max |z|	MS max |z|
Australia	3,782	27.12	28.45	18.80
Canada	3,761	27.69	28.51	20.40
France	3,839	30.17	31.05	22.64
Germany	3,809	29.51	30.44	21.05
Hong Kong	3,697	28.05	29.50	20.94
Israel	3,606	27.38	28.83	19.58
Japan	3,675	33.20	34.59	23.61
Sweden	3,766	29.46	30.39	21.71
UK	3,788	29.61	30.57	21.41
US	3,771	29.70	31.25	20.63
Brazil	3,705	27.53	28.42	19.76
Chile	3,736	23.66	25.46	15.43
China	3,642	26.98	28.36	19.35
Greece	3,712	25.31	26.55	17.53
India	3,704	25.89	27.23	18.27
Malaysia	3,686	25.16	26.59	18.02
Mexico	3,758	24.77	25.89	18.01
Poland	3,732	26.92	27.89	18.33
Russia	3,723	27.21	28.41	18.57
South Africa	3,735	27.85	28.85	20.54

Table 3.
Results of joint rank, rank score and sign tests based on daily returns

Note(s): 1. This table shows the daily return results of the Joint Rank (MR1), Rank Score (MR2) and Sign (MS) tests. Test probabilities are computed using permutation bootstrap. All the presented Max |z| values are statistically significant (different from 1)
2. The results strongly reject the null hypothesis of a random walk (rank and rank score tests) or the null hypothesis of a martingale (sign test) for all markets

We considered the possibility that stock market returns may not follow a random walk or a martingale due to non-synchronous trading as a result of lower liquidity. Given that such transient factors may not be as pronounced in lower frequency data, we repeated all the above tests using five-day interval data as a form of robustness checking. The results shown in Tables A1 and A2 in the appendix are consistent with those obtained using daily data, and we still reject the null of random walk (Rank and Rank Score tests) or a martingale (Chow–Denning tests and Sign test) across all markets. However, it is noticeable that the Max |z| statistics in lower frequency data are uniformly lower than the daily data ones, which may suggest less prominent predictability in lower frequency data.

5.2 VAR models

Having obtained empirical evidence that the sampled markets do not follow a random walk or a martingale pricing process, we now delve deeper into the nature of any predictability in the sampled data. Prior to estimating the bivariate VARs which model the relationships between the respective country indices and ACWI, the Akaike Information Criterion (AIC) was used to determine the optimal number of lags [4]. We do not report the VAR models in their entirety, and given that we are interested in the relative predictability of the respective country markets, we abstract from the section of the VAR where the ACWI Index is modelled as a function of its lags and the lags of a country index. For the sake of easier interpretation, we report the country index equation in two separate tables. The coefficients of the lags of the respective country index are shown in Table 4 (Panel A for established markets and Panel B for emerging markets) whereas Table 5 shows the section of the VARs pertaining to the lags of the ACWI.

Considering the first section of the VARs where the country index returns are modelled as a function of their own lags, we may note that there is a higher tendency for significant

delayed feedback in established markets. For instance, the first lag is significant (at least at the 90% level) in case of all established markets, whereas only six emerging markets feature such significance at the first lag. Similarly, there is a higher tendency for statistical significance of the subsequent lags in established markets. Indeed, the fact that the lag

	Intercept	Lag (−1)	Lag (−2)	Lag (−3)	Lag (−4)	Lag (−5)	Lag (−6)
Panel A: (established markets)							
Australia	4.5E-05	−0.3843	−0.0469	−0.0781	0.0006	−0.0124	
	0.21	−18.47***	−2.13**	−3.54***	0.03	−0.66	
Canada	0.0001	−0.0880	−0.0319	0.0439	0.0007	−0.0132	
	0.53	−3.12***	−1.12	1.54	0.02	−0.47	
France	−4.1E-05	−0.4470	−0.0815	−0.1002	−0.0011	−0.0595	
	−0.17	−15.23***	−2.63***	−3.23***	−0.03	−2.03**	
Germany	0.0002	−0.2769	−0.0168	−0.0788	0.0195	0.0008	0.0673
	1.04	−9.60***	−0.56	−2.64***	0.65	0.03	2.33**
Hong Kong	0.0001	−0.2988	−0.0758	−0.0594	−0.0374	−0.0300	
	0.57	−15.70***	−3.85***	−3.02***	−1.90*	−1.68*	
Israel	0.0003	0.0301	0.0172	−0.0319	−0.0048		
	1.29	1.82*	1.04	−1.93*	−0.29		
Japan	0.0001	−0.4225	−0.1505	−0.0525			
	0.71	−24.51***	−8.18***	−3.34***			
Sweden	0.0001	−0.3440	−0.1290	−0.1024	−0.0690	−0.0591	
	0.38	−13.05***	−4.74***	−3.76***	−2.55**	−2.24**	
UK	−0.0001	−0.4581	−0.1260	−0.0988	−0.0531	−0.1413	
	−0.47	−15.80***	−4.08***	−3.20***	−1.73*	−4.88***	
US	0.0003	−0.1621	−0.1144	0.0176	−0.0736	−0.0121	
	1.42	−4.14***	−2.65***	0.40	−1.71*	−0.34	

	Intercept	Lag (−1)	Lag (−2)	Lag (−3)	Lag (−4)	Lag (−5)
Panel B: (emerging markets)						
Brazil	0.0003	−0.0131	0.0024	−0.0430		
	0.74	−0.58	0.11	−1.88*		
Chile	0.0003	0.0959	0.0186	−0.0146	0.0065	−0.0259
	1.19	4.43***	0.86	−0.67	0.30	−1.20
China	0.0002	−0.0142	−0.0163			
	0.57	−0.84	−0.97			
Greece	−0.0004	0.0399	−0.0387			
	−1.25	2.17**	−2.10**			
India	0.0003	−0.0433	−0.0737	−0.0178		
	1.20	−2.31**	−3.94***	−0.96		
Malaysia	0.0001	0.0055	−0.0434	0.0019	0.0151	
	0.77	0.33	−2.65***	0.12	0.98	
Mexico	0.0002	0.0151	0.0049	−0.0771	−0.0711	
	0.92	0.70	0.23	−3.59***	−3.33***	
Poland	0.0001	−0.0460	0.0154	−0.0021	−0.0375	
	0.18	−2.14**	0.72	−0.10	−1.75*	
Russia	3.7E-05	−0.0954	−0.0574	−0.0425	0.0148	0.0093
	0.10	−4.72***	−2.83***	−2.09**	0.73	0.46
South Africa	0.0002	−0.1853	0.0509	−0.0285		
	0.68	−7.83***	2.12**	−1.21		

Note(s): The table reports the first set of coefficients for the country index equation in the VAR models, where the index is modelled as a function of its own lags

Coefficients are shown on top and *t*-ratios are reported underneath. Statistical significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively

Table 4.
Coefficients and *t*-ratios for country index lags in VAR models

	Lag (−1)	Lag (−2)	Lag (−3)	Lag (−4)	Lag (−5)	Lag (−6)	F-stat
Panel A: (established markets)							
Australia	9.8E-01	0.1254	0.0718	0.0713	−0.0195		128.30
	35.12***	3.81***	2.16**	2.16**	−0.60		
Canada	0.2324	−0.0104	−0.0443	0.0212	−0.1128		7.74
	5.76***	−0.26	−1.09	0.52	−2.82***		
France	8.1E-01	−0.0238	0.0748	0.0110	−0.0008		37.23
	17.93***	−0.50	1.57	0.23	−0.02		
Germany	0.5559	−0.0854	0.0736	−0.0295	−0.0792	−0.0774	16.80
	12.60***	−1.88*	1.62	−0.65	−1.75*	−1.75*	
Hong Kong	0.7678	0.0836	0.1468	−0.0078	0.0672		91.67
	29.73***	2.90***	5.07***	−0.27	2.33**		
Israel	−0.0182	0.0370	0.0331	0.0521			2.59
	−0.81	1.65*	1.47	2.33**			
Japan	0.8392	0.1770	0.1262				278.72
	38.46***	6.86***	4.88***				
Sweden	0.6840	0.0761	0.0559	0.1179	−0.0354		27.19
	14.87***	1.61	1.18	2.50***	−0.76		
UK	0.7433	0.0427	0.0599	0.0587	0.1002		42.76
	19.23	1.04	1.45	1.43	2.51**		
US	0.0843	0.0386	−0.0118	0.0647	−0.0652		7.07
	1.80	0.81	−0.25	0.05	−1.70*		

	Lag (−1)	Lag (−2)	Lag (−3)	Lag (−4)	Lag (−5)	F-stat
Panel B: (emerging markets)						
Brazil	0.1729	−0.1121	−0.0047			4.87
	3.13***	−2.02**	−0.09			
Chile	0.0732	−0.0218	−0.0442	0.0585	−0.0571	9.56
	2.48**	−0.73	−1.49	1.97**	−1.93*	
China	0.2768	−0.0272				23.98
	9.60***	−0.93				
Greece	0.2393	0.0028				17.04
	5.99***	0.07				
India	0.3904	0.0868	0.1036			31.37
	12.18***	2.67***	3.17***			
Malaysia	0.2247	0.2327	0.1123	0.0529		80.47
	15.19***	15.14***	7.11***	3.33***		
Mexico	0.2929	−0.1059	0.0515	0.1083		21.20
	8.30***	−2.97	1.44***	3.05		
Poland	0.3739	−0.1298	−0.0065	0.0387		13.48
	8.75***	−3.01***	−0.15	0.90		
Russia	4.9E-01	0.0964	0.0040	0.0455	−0.0836	12.77
	10.19***	1.97**	0.08	0.93	−1.71*	
South Africa	0.6006	−0.2280	−0.0418			40.97
	13.88***	−5.14***	−0.94			

Table 5.
Coefficients and
t-ratios for world-index
lags in VAR models

Note(s): The table reports the second set of coefficients for the country index equation in the VAR models, where the index is modelled as a function of the lags of the global index
Coefficients are shown on top and t-ratios are reported underneath. Statistical significance at the 99%, 95% and 90% level of confidence is denoted by ***, ** and * respectively

selection criterion suggested more lags for the established markets as compared to the emerging ones, also hints at a higher tendency for serial dependencies. When inspecting the signs of the lag coefficients, we may note a predominance of negative occurrences, particularly in case of established markets. This suggests that there may be a tendency for

the partial reversals of returns, which may either hint at over-reactions to news or at the reversal of liquidity-related price impacts, for instance following the execution of block transactions [5].

When inspecting the second section of the individual country index models (Table 5), we note that the significant coefficients denote delayed adjustments to fluctuations in ACWI and this is particularly evident for emerging markets when considering the first two lags. This is somewhat in line with the findings of Al-Thaqeb (2018) that various markets tend to under-react to favourable events in the US. With reference to our results, it is pertinent to note that the sign of the coefficients of the first ACWI lag is invariably positive, although there is a predominance of negative coefficients in the second lag (for emerging markets) and in the fifth lag (for both groups). The latter dependency may be consistent with an end-of-the-week effect.

Whilst significant coefficients in the VARs confirm the idea of predictability in both groups of markets, Tables 4 and 5 indicate that the nature of the predictability differs across the respective categories. In case of established markets, the serial dependencies within the individual-country indices seem more significant and they are predominantly negative. This suggests that one cause of predictability in established markets emanates from return reversals which may be due to the correction of liquidity-related price impacts or prior overreactions. As for emerging markets there seems to be a higher tendency for delayed adjustments to ACWI, particularly in case of the first lag. Although one may argue that this tendency may be partly attributed to time-zone differences, when grouping the emerging markets into three zones (Americas, Europe and Asia), we noted highly significant *t*-ratios across all groups, suggesting that time-zone differences on their own do not fully account for such dependency.

As discussed above, one may expect the impact of transient effects such as overreactions and non-synchronous trading to be more subtle in lower frequency data, and prior research such as Liu (2019) suggests that the impacts of lagged returns may vary when considering different data frequencies. In this way we re-estimated Granger-Causality models on data which were re-sampled at five-trading day intervals. The significant lags and their signs are summarised in Table 6. Established markets feature a marginally higher occurrence of significant lags as compared to emerging markets; considering the insights presented by Griffin *et al.* (2010), a higher element of predictability for established markets may not necessarily be indicative of lower efficiency since this may be due to differences in the underlying information generation process.

In case of established markets, we still note a tendency for the fluctuations of the respective country indices to be negatively related to their first lag. This suggests that reversals of overreactions or liquidity-related price impacts may be more prolonged than one or two days. Most of the established market index fluctuations are positively correlated to ACWI, suggesting that the impact of international occurrences may take considerably long to be fully reflected in stock prices.

In case of emerging markets, the tendency for the country indices to be positively related to their lags becomes less pronounced when using lower-frequency data. This suggests that any delayed reactions would have been corrected over longer time intervals, and/or any apparent causality that could have been the result of non-synchronous trading becomes less detectable. At this data frequency, there is still a tendency for positive causality from the lagged ACWI to the respective country indices, although considering the number of lags and their significance this feature seems marginally lower when compared to established markets. There could be various reasons why emerging markets seem to take longer to respond to international occurrences. One possibility is that these economies may be less open, and therefore spillover effects may not be as strong. Secondly, if emerging markets are indeed less stable, their stock indices may be more prone to individual country "noise" which

| Country | VAR lag | Significant lags in country index equation | |
		Country index lags	World index lags
Australia	3	1 − ***	1+ ***, 3 + ***
Canada	1	−	−
France	2	−	−
Germany	3	−	3 + *
Hong Kong	1	1 − **	1 + **
Israel	5	1 − **, 3 + *	1 + ***
Japan	1	1 − ***	1 + ***
Sweden	4	1 − ***, 2- **, 4 + **	2 + *, 4 − ***
UK	2	1 − ***, 2 − ***	1 + ***, 2 + **
US	2	1 − ***, 2 + ***	1 + ***, 2 − ***
Brazil	3	1 − ***, 2 + ***	2 − **
Chile	4	3 + **, 4 − **	4 + *
China	1	−	1 + ***
Greece	3	3 + **	2 + **, 3 + *
India	4	1 − ***, 2 + *	1 + ***
Malaysia	1	−	1 + ***
Mexico	1	1 − *	−
Poland	1	−	−
Russia	1	1 − *	−
South Africa	2	2 − ***	2 + ***

Note(s): The table summarises the significance of the lags in the Country–Index equations of the VAR models. The number of lags in the VAR is shown in the second column, while the subsequent columns report information pertaining to the significant lags. In each of the last two columns, the number denotes the order of the lag (e.g.1 for first), followed by the sign of the coefficient, and statistical significance denoted by ***, ** and * for the 99%, 95% and 90% levels respectively

Table 6.
Significant Lags in Country–Index Equations in VAR Models estimated using five-day interval data

dampens the effect of any international spillovers. Differences in information costs may also affect the comovement of a given market with its overseas counterparts (Inaba, 2020).

Prior literature may supplement the interpretation of the insights regarding emerging markets' behaviour. In particular, despite that in the last few decades, emerging securities markets have become more interlinked with the rest of the world due to financial liberalisation and economic integration (De Roon and De Jong, 2005), the extent of integration of emerging markets with other capital markets is still far from complete (Arouri *et al.*, 2012). This may be due to specific structural and institutional country effects, such as asymmetric information, investment barriers, controlled exchange rate regimes, regulatory deficiencies and underdeveloped capital markets.

Overall, the estimations on lower frequency data confirm the main insights of the daily data VAR models. One particular intricacy of this set of VAR results seems thought-provoking when assessed in the context of the insights of Griffin *et al.* (2010) that efficiency or predictability comparisons across markets should account for differences in the underlying news patterns. In particular, when considering the first section of the models (where the returns for the indices were modelled as a function of their own lags) developed markets transpired to be more predictable – although this may be due to the fact that we did not account for the differences in news production across markets. Conversely, when considering the second section of the VARs (where returns for each index were modelled as a function of the ACWI returns), we noted higher predictability in emerging markets. This time results are in line with conventional expectations, given that the relevant news component is common to both groups, and therefore accounting for discrepancies in news production may be less important in this instance.

5.3 Runs tests

Our third approach towards assessing the predictability in the sampled markets consists of runs tests on daily data, as reported in Table 7. On average, established markets feature a higher number of runs as compared to emerging counterparts, and the difference in runs across groups proved significant at the 99% level when conducting a *t*-test. It is unlikely that the higher number of runs in established markets is wholly attributable to a higher number of observations within the sample period, since the latter difference across groups was only significant at the 90% level of confidence.

Adopting a standard yardstick of 95% level of confidence, we note that the null hypothesis of a random series is rejected in half of the cases for both emerging and established markets. When abstracting from those cases where the result of the runs test is insignificant, we note that all established markets feature a higher number of runs than what one may expect, whereas emerging markets tend to feature a lower number of runs than may be expected. This echoes the results of the VAR models, in that we may conjecture that predictability in the established markets emanates from price reversals (which result in a higher number of shorter runs) and conversely a lower number of runs for emerging markets is indicative of positive serial dependencies (for instance owing to a gradual adjustment to news or non-synchronous trading effects).

6. Conclusion

An understanding of the intricacies in the nature of predictability across different markets, is of fundamental importance to design coherent studies relating to this issue, particularly in view of the conflicting insights emanating from prior literature. In this paper we analysed the

	# Observations	# Runs	Z	p-value
Australia	3,783	1822	−2.196	0.028**
Canada	3,762	1827	−1.635	0.102
France	3,840	1999	2.569	0.010***
Germany	3,810	1955	1.641	0.101
Hong Kong	3,698	1871	0.762	0.446
Israel	3,672	1813	−0.614	0.539
Japan	3,676	2065	7.490	6.9E-14***
Sweden	3,767	1950	2.186	0.029**
UK	3,789	1943	1.711	0.087
US	3,772	2013	4.304	1.7E-05***
Brazil	3,706	1798	−1.786	0.074*
Chile	3,737	1,650	−7.140	9.4E-13***
China	3,643	1805	−0.460	0.645
Greece	3,714	1,695	−5.216	1.8E-07***
India	3,705	1722	−4.183	2.9E-05***
Malaysia	3,690	1,660	−6.107	1.0E-09***
Mexico	3,760	1737	−4.517	6.3E-06***
Poland	3,733	1881	0.479	0.632
Russia	3,724	1837	−0.790	0.430
South Africa	3,736	1868	0.039	0.969

Note(s): The table summarises the results of the runs tests on the null hypothesis that the log returns of the index for each sampled country are generated in a random manner. The second and third columns show the number of observations and the number of runs in the time series respectively. The fourth column shows the *z*-statistic of the runs test. The last column denotes statistical significance with the *p*-value followed by ***, ** and * for the 99%, 95% and 90% levels respectively

Table 7.
Runs tests

predictability differences across developed and emerging markets, given that the latter group often feature distinct characteristics such as lower liquidity, higher commonality in liquidity, higher volatility and higher return predictability (Bekaert and Harvey, 1997; Hung, 2009). In view of this, one may expect that the price formation process in emerging markets may differ when compared to that of established counterparts. Nonetheless, when considering that emerging markets have become more open to liberalisation and are adopting recent technologies and upgrading information disclosure standards, this hypothesis should not be taken for granted. We delved into this issue by inquiring whether there are any underlying differences in the nature of the predictability of the pricing process in a sample of ten established markets and ten emerging ones.

Comparisons between developed and emerging markets were not frequently tackled in past studies and these were usually conducted with the objective of inferring differences in market efficiency between the respective groups rather than in terms of delving into the nature of predictability. In view of the insights obtained by Griffin *et al.* (2010) we refrain from attempting to conjecture which of the respective market groups is more efficient – rather our objective was to assess how predictability may differ across markets.

We conducted VR tests which rejected the null hypothesis that index fluctuations follow a random walk or a martingale for different data frequencies. We then estimated VAR models to focus on specific serial dependencies both within the individual country indices and the lagged effects from international markets. Next, we conducted runs tests to elaborate on and cross-check the observed tendencies. Negative lags in the indices of established markets suggest the reversals of overreactions to news or liquidity-related transitions, and this is corroborated by the finding that these indices tend to feature a higher number of runs than one would expect in a random series. When such serial dependencies were modelled through VAR models using five-day interval data, there still was a tendency for the fluctuations of the respective country indices to be negatively related to their first lag, which hints that such reversals tend to be quite prolonged. Possibly this indicates that such dependencies are caused by information-related factors rather than liquidity-related ones.

Conversely, the VAR models for emerging markets suggest that the latter react to international developments with a delay, and such finding is corroborated by runs tests which indicate that overall these markets feature a lower number of runs than one may expect in a randomly-generated series. Such "lagged reactions" were still evident when re-estimating the models using lower frequency data, suggesting that the positive serial dependencies are not merely the results of non-synchronous trading which one would expect to be less manifest at lower frequencies. These tendencies for emerging markets were observed across different geographic regions, hinting that such lagged effects are not wholly attributable to time-zone differences.

Our selection of parametric and non-parametric tests implies that we did not over-rely on the assumption of normally distributed data. Our results are noteworthy on various accounts. Firstly, they confirm the hypothesis that there are substantial differences in predictability across developed and emerging markets, and secondly, they indicate that the disparities in the nature of predictability are likely to emanate from different sources across these groups. An understanding of such differences is important in designing further studies relating to this issue, in the sense that researchers should be aware that treating predictability as a uniform concept across a sample of markets is unlikely to incorporate the required refinements for a thorough investigation. In addition, our results augment the empirical evidence presented by Griffin *et al.* (2010) through the use of updated data which encompasses more recent material events.

Given that the evidence points that the predictability varies across the groups in the sense that we mainly note negative (positive) serial dependencies for developed (emerging) markets, our findings suggest that it is important to account for the underlying news process

given that the reaction to news seems to differ across the groups. This is in line with the earlier observations of Griffin *et al.* (2010). Indeed, the underlying news patterns may explain salient aspects which we noticed in our VAR results. In particular, when considering the first section of the models (where returns for each index were modelled as a function of its own lags) developed markets transpire to be more predictable – although this may be due to the fact that we do not account for the discrepancy in news production across markets as suggested by Griffin *et al.* (2010). Conversely, when considering the second section of the VARs (where returns for the particular index were modelled as a function of the ACWI returns), we noted higher predictability in emerging markets. The fact that the latter results are in line with conventional wisdom that emerging markets are less efficient, may be due to the fact that the relevant news component is common to both groups, and therefore accounting for discrepancies in news production may be less crucial in this particular context.

If we rule out liquidity-related explanations behind the observed predictability (on the grounds that the observed dependencies were still evident in lower-frequency data), it would seem that the predictability in emerging markets emanates from delayed price adjustments, whereas in case of established markets one may think of price reversals following over-reactions. One possibility is that lower trading costs have made day-trading accessible to a broader selection of participants in established markets, who may be quick to respond to news, but then over-react owing to the sheer volume of trading.

The above insights should be interpreted in the context of the inherent limitations of the study. In particular, when analysing data sets which span over longer periods as in case of this study, the intricacies which affect the pricing process are prone to change due to factors such as revised trading protocols (Camilleri, 2015), volatility spillovers (Camilleri, 2010), and other economic and financial reforms (Roy and Shijin, 2020). Finally, we note that when applying uniform models to assess return predictability for different countries, the idiosyncratic factors which may be relevant to any given market are de-emphasised even though they may add a pertinent contribution (Hadri and Ftiti, 2017).

The findings of this study pinpoint at further research potential especially in view of the asymmetric results which were obtained for the respective market groups. First of all, further evaluation is warranted to our interpretation that traders tend to overreact in established markets while they may be less responsive in emerging markets, and the factors that may cause such tendencies may be delved into. The increased trends for electronic trading, high-frequency trading, and algorithmic trading in established markets (Dutta *et al.*, 2017; Goldstein *et al.*, 2014) could be one possibility which accounts for the former behaviour. In addition, differences in the costs of obtaining and interpreting information across the market groups could account for the likelihood of over- or under-reactions (Inaba, 2020). Related to these ideas are the issues of whether such market behaviour may be profitably exploited, and whether any overreactions may emanate from analysts' recommendations, social influence, and / or feedback trading (Tambakis, 2006).

Notes

1. Israel was not classified as a developed market during the whole sample period, but it was classified as such at the date of sampling.

2. The tests which we use in this paper are closely linked to the aspect of market efficiency on the grounds that in an efficient market, traders endeavour to price in any aspects which may be predictable. Having said this, our results should not be interpreted as a direct comparison of the efficiency across markets, since as per Griffin *et al.* (2010) a coherent investigation of this issue would entail accounting for differences in the information-generation process between the respective groups. Rather, our main objective is to assess whether salient aspects of predictability differ materially across developed and emerging markets.

3. Richardson and Stock (1989) suggested that asymptotic distribution might lead to misleading statistical inference due to severe size distortion, low power, and rights-skewness biases especially when the sample size is too small to justify the asymptotic approximations.

4. For the sake of parsimony, we started with an initial lag value of five; in this way we assumed that news will not take more than five days to spill-over between the selected indices. Given that indices typically consist of the most liquid stocks of the market we think that this is a reasonable assumption. We then selected the optimum lag length as per the AIC. In case of the German Index, a five-lag VAR resulted in serially correlated residuals, and therefore a six-lag VAR was used.

5. Negative serial dependencies in individual stock data are at times attributed to the bid-ask spread bounce, yet such effect may not induce material negative correlation in index data since in a cross-section of stocks, one may expect that the effect of prices bouncing from the ask to the bid would be counterbalanced by other prices which change in the opposite direction.

References

Abrosimova, N., Dissanaike, G. and Linowski, D. (2002), "Testing weak-form efficiency of the Russian stock market", *Paper Presented at the EFA 2002 Berlin Meetings*.

Al Nasser, O.M. and Hajilee, M. (2016), "Integration of emerging stock markets with global stock markets", *Research in International Business and Finance*, Vol. 36, pp. 1-12.

Al-Thaqeb, S.A. (2018), "Do international markets overreact? Event study: international market reaction to US local news events", *Research in International Business and Finance*, Vol. 44, pp. 369-385.

Alexakis, C., Patra, T. and Poshakwale, S. (2010), "Predictability of stock returns using financial statement information: evidence on semi-strong efficiency of emerging Greek stock market", *Applied Financial Economics*, Vol. 20 No. 16, pp. 1321-1326.

Arouri, M.E.H., Nguyen, D.K. and Pukthuanthong, K. (2012), "An international CAPM for partially integrated markets: theory and empirical evidence", *Journal of Banking and Finance*, Vol. 36 No. 9, pp. 2473-2493.

Bekaert, G. and Harvey, C.R. (1997), "Emerging equity market volatility", *Journal of Financial Economics*, Vol. 43 No. 1, pp. 29-77.

Berkman, H. (1996), "Large option trades, market makers, and limit orders", *The Review of Financial Studies*, Vol. 9 No. 3, pp. 977-1002.

Borges, M.R. (2010), "Efficient market hypothesis in European stock markets", *The European Journal of Finance*, Vol. 16 No. 7, pp. 711-726.

Boya, C.M. (2019), "From efficient markets to adaptive markets: evidence from the French stock exchange", *Research in International Business and Finance*, Vol. 49, pp. 156-165.

Camilleri, S.J. (2006), "An analysis of stock index distributions of selected emerging markets", *Bank of Valletta Review*, Vol. 33, pp. 33-49.

Camilleri, S.J. (2010), "Response of Indian equities to US stock market movements of the prior trading day", in Gregoriou, G.N. (Ed.), *Emerging Markets: Performance, Analysis and Innovation*, CRC Press – Taylor and Francis Group, Florida, pp. 493-508.

Camilleri, S.J. (2015), "Do call auctions curtail price volatility? Evidence from the national stock exchange of India", *Managerial Finance*, Vol. 41 No. 1, pp. 67-79.

Camilleri, S.J. and Galea, G. (2009), "The diversification potential offered by emerging markets in recent years", *The FEMA Research Bulletin*, Vol. 1 No. 3, pp. 21-37.

Camilleri, S.J. and Green, C. (2014), "Stock market predictability: non-synchronous trading or inefficient markets? evidence from the national stock exchange of India", *Studies in Economics and Finance*, Vol. 31 No. 4, pp. 354-370.

Camilleri, S.J., Scicluna, N. and Bai, Y. (2019), "Do stock markets lead or lag macroeconomic variables? Evidence from select European countries", *The North American Journal of Economics and Finance*, Vol. 48, pp. 170-186.

Campbell, J.Y., Lo, A.W. and MacKinlay, A.C. (1997), *The Econometrics of Financial Markets*, Princeton University Press, Princeton, New Jersey, NJ.

Chow, K.V. and Denning, K.C. (1993), "A simple multiple variance ratio test", *Journal of Econometrics*, Vol. 58 No. 3, pp. 385-401.

Daniel, K. and Titman, S. (1999), "Market efficiency in an irrational world", *Financial Analysts Journal*, Vol. 55 No. 6, pp. 28-40.

Davidson, R. and Flachaire, E. (2008), "The wild bootstrap, tamed at last", *Journal of Econometrics*, Vol. 146 No. 1, pp. 162-169.

De Roon, F. and De Jong, F. (2005), "Time-varying market integration and expected returns in emerging markets", *Journal of Financial Economics*, Vol. 78, pp. 583-613.

Dhakal, D., Kandil, M. and Sharma, S.C. (1993), "Causality between the money supply and share prices: a VAR investigation", *Quarterly Journal of Business and Economics*, Vol. 32 No. 3, p. 52.

Dutta, S., Essaddam, N., Kumar, V. and Saadi, S. (2017), "How does electronic trading affect efficiency of stock market and conditional volatility? Evidence from Toronto stock exchange", *Research in International Business and Finance*, Vol. 39, pp. 867-877.

Escha, D.N. (2010), "Non-normality facts and fallacies", *Journal of Investment Management*, Vol. 8 No. 1, pp. 49-61.

Fifield, S.G. and Jetty, J. (2008), "Further evidence on the efficiency of the Chinese stock markets: a note", *Research in International Business and Finance*, Vol. 22 No. 3, pp. 351-361.

Freund, W.C. and Pagano, M.S. (2000), "Market efficiency in specialist markets before and after automation", *Financial Review*, Vol. 35 No. 3, pp. 79-104.

Goldstein, M.A., Kumar, P. and Graves, F.C. (2014), "Computerized and high-frequency trading", *Financial Review*, Vol. 49 No. 2, pp. 177-202.

Granger, C.W.J. (1969), "Investigating causal relations by econometric models and cross-spectral methods", *Econometrica*, Vol. 37 No. 3, pp. 425-438.

Griffin, J.M., Kelly, P.J. and Nardari, F. (2010), "Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets", *The Review of Financial Studies*, Vol. 23 No. 8, pp. 3225-3277.

Gu, A.Y. and Finnerty, J. (2002), "The evolution of market efficiency: 103 years daily data of the Dow", *Review of Quantitative Finance and Accounting*, Vol. 18 No. 3, pp. 219-237.

Hadri, S. and Ftiti, Z. (2017), "Stock return predictability in emerging markets: does the choice of predictors and models matter across countries?", *Research in International Business and Finance*, Vol. 42, pp. 39-60.

Hung, J.C. (2009), "Deregulation and liberalization of the Chinese stock market and the improvement of market efficiency", *The Quarterly Review of Economics and Finance*, Vol. 49 No. 3, pp. 843-857.

Inaba, K.I. (2020), "Information-driven stock return comovements across countries", *Research in International Business and Finance*, Vol. 51, pp. 1-8.

Kandel, E., Rindi, B. and Bosetti, L. (2012), "The effect of a closing call auction on market quality and trading strategies", *Journal of Financial Intermediation*, Vol. 21 No. 1, pp. 23-49.

Kaniel, R., Saar, G. and Titman, S. (2008), "Individual investor trading and stock returns", *Journal of Finance*, Vol. 63 No. 1, pp. 273-310.

Kim, J.H. (2006), "Wild bootstrapping variance ratio tests", *Economics Letters*, Vol. 92 No. 1, pp. 38-43.

Lee, Y., Liu, Y., Roll, R. and Subrahmanyam, A. (2004), "Order imbalances and market efficiency: evidence from the Taiwan stock exchange", *Journal of Financial and Quantitative Analysis*, Vol. 39 No. 2, pp. 327-41.

Liu, J. (2019), "Impacts of lagged returns on the risk-return relationship of Chinese aggregate stock market: evidence from different data frequencies", *Research in International Business and Finance*, Vol. 48, pp. 243-257.

Lo, A.W. (2004), "The adaptive markets hypothesis: market efficiency from an evolutionary perspective", *Journal of Portfolio Management*, Vol. 30, pp. 15-29.

Lo, A.W. and MacKinlay, A.C. (1988), "Stock market prices do not follow random walks: evidence from a simple specification test", *The Review of Financial Studies*, Vol. 1 No. 1, pp. 41-66.

Lo, A.W. and MacKinlay, A.C. (1989), "The size and power of the variance ratio test in finite samples: a Monte Carlo investigation", *Journal of Econometrics*, Vol. 40 No. 2, pp. 203-238.

Lo, A.W. and MacKinlay, A.C. (1999), *A Non-random Walk Down Wall Street*, Princeton University Press, Princeton, New Jersey, NJ.

Lu, C., Wang, K., Chen, H. and Chong, J. (2007), "Integrating A-and B-share markets in China: the effects of regulatory policy changes on market efficiency", *Review of Pacific Basin Financial Markets and Policies*, Vol. 10 No. 3, pp. 309-328.

Mackinnon, J.G. (2002), "Bootstrap inference in econometrics", *Canadian Journal of Economics/Revue Canadienne d'Économique*, Vol. 35 No. 4, pp. 615-645.

Maddala, G.S. and Wu, S. (1999), "A comparative study of unit root tests with panel data and a new simple test", *Oxford Bulletin of Economics and Statistics*, Vol. 61 No. 4, pp. 631-652.

Mohti, W., Dionísio, A., Vieira, I. and Ferreira, P. (2019), "Regional and global integration of Asian stock markets", *Research in International Business and Finance*, Vol. 50, pp. 357-368.

Narayan, P.K. and Smyth, R. (2007), "Mean reversion versus random walk in G7 stock prices evidence from multiple trend break unit root tests", *Journal of International Financial Markets, Institutions and Money*, Vol. 17 No. 2, pp. 152-166.

Nisar, S. and Hanif, M. (2011), "Testing weak form of efficient market hypothesis: empirical evidence from South Asia", *World Applied Sciences Journal*, Vol. 17 No. 4, pp. 414-427.

Pernagallo, G. and Torrisi, B. (2020), "Blindfolded monkeys or financial analysts: who is worth your money? new evidence on informational inefficiencies in the US stock market", *Physica A: Statistical Mechanics and Its Applications*, p. 539.

Poterba, J. and Summers, L. (1988), "Mean reversion in stock prices: evidence and implications", *Journal of Financial Economics*, Vol. 22 No. 1, pp. 27-59.

Piccoli, P., Chaudhury, M., Souza, A. and Vieira da Silva, W. (2017), "Stock overreaction to extreme market events", *The North American Journal of Economics and Finance*, Vol. 41, pp. 97-111.

Richardson, M. (1993), "Temporary components of stock prices: a skeptic's view", *Journal of Business and Economic Statistics*, Vol. 11 No. 2, pp. 199-207.

Richardson, M. and Stock, J.H. (1989), "Drawing inferences from statistics based on multiyear asset returns", *Journal of Financial Economics*, Vol. 25 No. 2, pp. 323-348.

Roy, R. and Shijin, S. (2020), "A tripartite inquiry into financial liberalization-volatility-information asymmetry nexus: global panel approach", *IIMB Management Review*, Vol. 32 No. 1, pp. 39-58.

Srivastava, A. (2007), "Comparison of weak form of market efficiency of developed stock markets with emerging Asian markets", *Paradigm*, Vol. 11 No. 1, pp. 13-19.

Tambakis, D.N. (2006), *Can Feedback Traders Rock the Markets? A Logistic Tale of Persistence and Chaos*, CFAP, University of Cambridge, Cambridge Judge Business School, Cambridge.

Vo, X.V. (2017), "Do foreign investors improve stock price informativeness in emerging equity markets? Evidence from Vietnam", *Research in International Business and Finance*, Vol. 42, pp. 986-991.

Worthington, A. and Higgs, H. (2006), "Weak-form market efficiency in Asian emerging and developed equity markets: comparative tests of random walk behaviour", *Accounting Research Journal*, Vol. 19 No. 1, pp. 54-63.

Wright, J.H. (2000), "Alternative variance-ratio tests using ranks and signs", *Journal of Business and Economic Statistics*, Vol. 18 No. 1, pp. 1-9.

Yılmaz, M.K., Erdem, O., Eraslan, V. and Arık, E. (2015), "Technology upgrades in emerging equity markets: effects on liquidity and trading activity", *Finance Research Letters*, Vol. 14, pp. 87-92.

Further reading

Fama, E.F. (1965), "The behavior of stock-market prices", *The Journal of Business*, Vol. 38 No. 1, pp. 34-105.

Appendix

Market	Dof	Homoscedasticity robust test statistics max |z|		Heteroscedasticity robust test statistics max |z|	
		Panel A	Panel B	Panel A	Panel B
Australia	755	14.08	14.08	4.98	4.98
Canada	751	14.03	14.03	5.34	5.34
France	767	14.17	14.17	7.76	7.76
Germany	761	15.16	15.16	8.28	8.28
Hong Kong	738	13.77	13.77	8.37	8.37
Israel	720	13.16	13.16	7.11	7.11
Japan	734	14.97	14.97	5.34	5.34
Sweden	752	15.19	15.19	5.50	5.50
UK	756	14.23	14.23	8.39	8.39
US	753	16.90	16.90	5.44	5.44
Brazil	740	16.12	16.12	7.08	7.08
Chile	746	14.52	14.52	6.77	6.77
China	727	13.57	13.57	10.18	10.18
Greece	741	14.16	14.16	7.31	7.31
India	740	15.37	15.37	8.72	8.72
Malaysia	736	14.01	14.01	6.77	6.77
Mexico	750	15.77	15.77	6.18	6.18
Poland	745	14.30	14.30	7.22	7.22
Russia	743	14.60	14.60	6.85	6.85
South Africa	746	13.37	13.37	7.72	7.72

Note(s): 1. This table presents five-day return results of Chow–Denning tests (test of martingale hypothesis). The presented are Max $|z|$ with probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

2. All the test statistics are statistically significant (different from 1), using a critical value of 2.49 (panel A) and using the confidence intervals calculated with the Wild Bootstrapping method (panel B)

3. The results strongly reject the null hypothesis of a martingale across all markets

4. We also ran the above tests in panel settings under the assumption that cross-sections are independent, with cross-section heterogeneity of the processes. The combined the p-values from cross-section results using the Fisher approach as in Maddala and Wu (1999) were all highly significant for both developed and emerging market panels

Table A1.
Chow–denning joint variance ratio test results based on five-day returns

Market	Dof	MR1 max $|z|$	MR2 max $|z|$	MS max $|z|$
Australia	755	12.50	13.25	8.55
Canada	751	12.42	13.11	8.58
France	767	13.45	14.05	9.79
Germany	761	14.35	14.96	10.40
Hong Kong	738	13.04	13.57	9.57
Israel	720	12.87	13.28	9.24
Japan	734	13.42	14.15	8.64
Sweden	752	13.35	14.33	8.82
UK	756	13.98	14.44	10.26
US	753	14.81	16.02	10.82
Brazil	740	15.39	15.99	10.22
Chile	746	13.01	13.99	8.20
China	727	13.85	13.82	10.05
Greece	741	12.76	13.70	9.74
India	740	14.15	14.97	10.37
Malaysia	736	12.46	13.33	8.55
Mexico	750	15.03	15.54	10.88
Poland	745	13.57	14.08	10.51
Russia	743	13.06	14.13	8.40
South Africa	746	12.39	13.26	8.71

Note(s): 1. This table presents the five-day return results of the Joint Rank (MR1), Rank Score (MR2) and Sign (MS) tests. Test probabilities are computed using permutation bootstrap. All the presented Max $|z|$ are statistically significant (different from 1)

2. The results strongly reject the null hypothesis of a random walk (Rank and Rank Score tests) or a martingale (Sign test) for all of the markets

3. We also ran the above tests in panel settings under the assumption that cross-sections are independent, with cross-section heterogeneity of the processes. The combined the p-values from cross-section results using the Fisher approach as in Maddala and Wu (1999) were all highly significant for both developed and emerging market panels

Table A2.
Results of Joint Rank, Rank Score and Sign tests based on five-day returns

Corresponding author
Silvio John Camilleri can be contacted at: silvio.j.camilleri@um.edu.mt