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RESEARCH ARTICLE

On the dynamics of international stock market efficiency

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Abstract: The Granger causality procedure is used to assess the dynamics of market efficiency of 17 international stock indices. These indices are based on relatively smaller firms. The reference of market efficiency is a stock index, from the same economy, which is based on relatively larger firms. There is evidence that market efficiency increases over time at a decreasing rate.

Keywords: market efficiency, international, stock indices, panel model, Granger causality

JEL classifications: G14, G15

1. Introduction

The transfer of information from one stock to another stock is a fundamental issue in the study of market efficiency. Since Lo and MacKinlay (1988, 1990), a regular observation is that the returns of small firms are correlated with the lagged returns of large firms after the lagged returns of the small firms are taken into account. The reverse is an infrequent occurrence. The implication is that the market efficiency of the shares of large firms is greater than the market efficiency of the shares of small firms. There are numerous explanations for this effect. Recent surveys are provided by Hou (2007), Karmakar (2010), and Chordia, Sarkar, and Subrahmanyam (2011). An important point is the possibility that the size of the firm may be a proxy for the magnitude of the information available to investors (Badrinath, Kale, & Noe, 1995, p. 402).

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PUBLIC INTEREST STATEMENT

Stock markets are efficient if any new information is incorporated almost immediately in the stock prices. If so, the future stock returns of small firms should not be predictable by using the current stock returns of the big firms. We find otherwise by using data for a panel of 17 developed stock markets. However, we also find that this predictability declines over time, suggesting that markets get more efficient as time goes by. A further finding is that the rate of such improvement slows down as full efficiency is approached. The implication is that market efficiency increases over time at a decreasing rate.

Market efficiency, i.e. the speed at which information is reflected in prices, is of vital importance to market regulators and market practitioners. As a result, the topic we explore is also of interest to academics. We contribute to the literature by examining the temporal change in the level of market efficiency (see Chordia, Sarkar, et al., 2011; Fargher & Weigand, 1998). The evidence points to the fact that market efficiency increases as time goes by. The implication for researchers is that a temporal dimension should be included in analyses of the factors that influence the level of market efficiency or the analyses of stock price anomalies.

Our focus is on the degree that the prices of large-cap stock indices lead the prices of small-cap stock indices during a period of 21 years. We use a panel data approach to simultaneously examine pairs of stock indices from 17 countries—the prior studies examine a single economy. The regression approach is based on the Granger (1969) causality model—also known as a vector auto regression model (e.g. Hou, 2007). This model generates a test statistic that can be interpreted as a relative measure of market efficiency. The large-cap index is used as the reference of market efficiency of the small-cap index. An important aspect is the use of a temporal indicator to assess the degree that Granger causality changes over time. We find evidence that the market efficiency of the small-cap indices increases over time at a decreasing rate.

2. Literature and Hypotheses

2.1. Literature Review

The Granger (1969) causality test is often used to determine the degree that futures prices lead spot prices (e.g. Bekiros & Diks, 2008; Kavussanos & Nomikos, 2003; Rittler, 2012; Schwarz & Szakmary, 1994). In the majority of cases, the observed Granger causality shows that the futures market acts as the market for price discovery for the spot asset. The reason for this is that the futures market is more efficient than the spot market. In a similar vein, there is evidence that the returns of stock indices (Dicle, Beyhan, & Yao, 2010; Gutierrez, Martinez, & Tse, 2009) or exchange-traded funds (Krause & Tse, 2013) of a small economy are Granger-caused by the returns of corresponding assets in a larger economy. Stock markets in the larger economies are characterized by greater transparency and lower transaction costs. Industry fundamentals and new information are reflected more quickly in such markets. Hence, the usual finding is that returns in the more efficient markets Granger-cause those in the less efficient ones. In other words, price discovery originates in the more efficient market.

There is evidence that stock market efficiency increases over time (Chordia, Roll, & Subrahmanyam, 2011; Fargher & Weigand, 1998; Gupta & Guidi, 2012). In an examination of the causality between the Indian BSE index and four international stock indices, Gupta and Guidi (2012, Figure 3, p. 19) report graphs of time varying contemporaneous correlations in the returns of these indices. The magnitude of the correlations increases over time. The graphs are strongly suggestive of increased economic integration between the Indian economy and the developed economies of Hong Kong, Japan, and the US over the period 1999–2009. The results could, in part, be attributed to a greater temporal increase in the market efficiency of the BSE index relative to the international stock indices.

Chordia, Roll, et al. (2011) examine the dynamics of market efficiency using Trade and Quote data from the New York Stock Exchange over the years 1993–2008. They observe an increase in the number of small trades, an increase in turnover, and a reduction in the cost of trading. Their conclusion is that "… prices conform more closely to random walk in recent years, indicating that market efficiency has increased …" (Chordia, Roll, et al., 2011, p. 261).

There is direct evidence that the magnitude of Granger causality of the returns of large firms on the returns of small firms decreases over time (Fargher & Weigand, 1998). Their data are obtained from the Centre for Research in Security Prices Daily Master File. Two portfolios, based on market capitalization, are created. One portfolio contains the top decile firms and the other portfolio contains the bottom decile firms. The period is 1972–1992—a sample of 7,675 daily returns. A dummy variable is used to differentiate the 1962–1975 period from the 1976–1992 period. The magnitude of Granger causality is observed to be lower in the second period.

2.2. Hypotheses

Keef, Khaled, and Zhu (2009), in a study of the Monday effect in 50 international stock indices, present evidence that is consistent with an increase in market efficiency over time. The focus is on the prior day anomaly (Tong, 2000). The sign of the return on the prior day is a good predictor of the sign of the return on the current day. On "good days"—those for which the return in the prior day is not negative—the return is enhanced. On "bad days"—those for which the return in the prior day is negative—the return is depressed. The difference in returns of good days compared to bad days is the measure of the prior day effect.

The magnitude of the prior day anomaly is a measure of market inefficiency. There is a size effect in the prior day anomaly. The anomaly is of greater magnitude for small underdeveloped (i.e. low per capita GDP) countries compared to the large developed (i.e. high per capita GDP) countries. It follows that the stock markets of large economies are more efficient than those of small economies. This leads to

$$\text{Axiom 1:} ME_t^{\text{Large}} > ME_t^{\text{Small}} \tag{1}$$

where ME_t represents the level of market efficiency at time t. Fargher and Weigand (1998) show that this axiom applies to large-cap stocks and small-cap stocks in the US.

Keef et al. (2009) offer two empirically derived findings on the temporal behavior of the prior day anomaly. The first finding is that the magnitude of the anomaly decreases over time for the average country in their sample. Stated in terms of market efficiency, this leads to

$$\text{Axiom 2:} \frac{dME_t}{dt} > 0 \tag{2}$$

i.e. market efficiency increases over time. There is evidence that the returns of stocks quoted on the New York Stock Exchange exhibit an increase in market efficiency over time (Chordia, Roll, et al., 2011). Similar evidence is presented by Gupta and Guidi (2012) for the Indian BSE index.

The second finding of Keef et al. (2009) is that the rate of the temporal reduction in the magnitude of the prior day anomaly is a function of the size of the economy. It is faster in less developed (small) economies compared to the developed (large) economies. Under Axioms 1 and 2, this can be formulated as

$$\text{Hypothesis H:} \frac{d^2ME_t}{dt^2} < 0 \tag{3}$$

In other words, the greater the inefficiency (or the less developed the economy), the faster the rate at which the inefficiency dissipates. This is the hypothesis we test.

The validity of the hypothesis can be established if there is an independently obtained statistic to measure the level of market efficiency. Market efficiency is a latent notion. Its level cannot be directly measured. We use Granger causality for this purpose. The subjects in this study are, for each country, a small-cap index. The corresponding large-cap stock index is used as the yardstick of market efficiency.

The Granger causality GC_t is a relative measure of market efficiency, that is, it can be viewed as the difference

$$GC_t = ME_t^{\text{Large}} - ME_t^{\text{Small}} \tag{4}$$

where subscript t refers to a period—one year with our study. Thus, the larger the Granger causality, the greater the relative inefficiency of the small-cap index. The expectation, given prior research

(Axiom 1), is that GC_t will be statistically greater than zero at the start of the data. The temporal change in the Granger causality is given by

$$\frac{dGC_t}{dt} = \frac{dME_t^{\text{Large}}}{dt} - \frac{dME_t^{\text{Small}}}{dt} \tag{5}$$

In essence, we have one equation with two unknowns in Equation 5. The primary focus is on the temporal change in the market efficiency of the small-cap index $\frac{dME_t^{\text{Small}}}{dt}$. To infer the dynamics of market efficiency from the change in Granger causality, it is necessary to make an appropriate assumption about the relative temporal change in the market efficiency of the reference large-cap index $\frac{dME_t^{\text{Large}}}{dt}$. For this, we invoke Axiom 1: $ME_t^{\text{Small}} < ME_t^{\text{Large}}$. Support for hypothesis H is found if there is a temporal decline in the Granger causality, $\frac{dGC_t}{dt} < 0$. That is,

$$\frac{dME_t^{\text{Small}}}{dt} > \frac{dME_t^{\text{Large}}}{dt} \tag{6}$$

Under Axiom 1, the implication of this faster improvement is convergence: $ME_t^{\text{Small}} \to ME_t^{\text{Large}}$. In other words, the improvement in ME_t^{Small} slows down as it approaches ME_t^{Large} from below. This supports hypothesis H.

We examine daily data. Thus, we are able to simultaneously examine the temporal change in the magnitude of Granger causality on non-Mondays and also on Mondays. There is stronger support for hypothesis H if two conditions are met for the Monday data. In terms of returns of stock indices and other assets, Mondays are anomalous. The first condition is that the magnitude of Granger causality on Mondays, at the start of the data in 1990, is larger than the magnitude of Granger causality on non-Mondays. The second condition is that the magnitude of Granger causality on Mondays declines over time at a faster rate compared to non-Mondays. The presence of these two conditions provides convincing confirmation of hypothesis H.

3. Method

3.1. Data

The stock index price series are obtained from Datastream. Our search isolated 17 countries where: (1) index price data for two indices are available for a period of 21 years (1 January 1990–31 December 2010) and (2) we could reliably classify one as being a large-cap index and the other as being an index with a lower capitalization. In this regard, our sample of countries is constrained by data availability. The countries can be assessed as being highly developed. The sample is conservative to the degree that a large change in market efficiency is not to be expected. Table 1 provides details of the indices. With 5,480 possible trading days for each country, there are 93,160 possible trading days in the period for our panel of the countries. After missing values are taken into account, 86,316 cases remain available for analysis.

It is possible that some may not agree with our choice of small-cap indices. Two illustrations are the FTSE All share index and the NYSE Composite. These are value-weighted indices. The important point is that they are based on smaller firms than their large-cap counterparts of FTSE 100 and Dow Jones Industrial, respectively. The fact that the size differential may not be large, argues that the reported results are biased towards the null hypothesis rather than against it. In this case, rejection of the null hypothesis offers stronger support for the alternative hypothesis.

Another potential criticism is the possible presence of non-synchronous trading in the constituent stocks of the indices. This will be more of a problem with the small-cap indices. There are three points to note. First, we examine the small-cap indices of major economies (see Table 1). Second, there does not

Table 1. Countries and Their Stock Indices

Country	Large-cap index	Small-cap index
Australia	S&P/ASX 20	S&P/ASX Small ord
Austria	DS Market (50 firms)	HSBC Smaller
Denmark	OMXC 20	S&P Small
Finland	DS Market (50 firms)	OMXH
France	CAC 40	DS Market (250 firms)
Germany	DAX 30	CDAX General
Hong Kong	Hang Seng	Hang Seng Small cap
Ireland	DS Market (50 firms)	S&P Small
Italy	Milan COMIT 30	Milan COMIT General
Japan	NIKKEI 225 Average	NIKKEI 500
Korea	SE Large-sized	SE Small-sized
Netherlands	AEX Index	Midkap
Singapore	FTSE W Singapore	S&P Small
Spain	IBEX 35	IBEX Medium cap
Sweden	OMXS 30	DS Market (70 firms)
UK	FTSE 100	FTSE All share
USA	Dow Jones Industrials	NYSE Composite

Note: The stock index price series are obtained from Datastream for a period of 21 years (1 January 1990–31 December 2010).

appear to be a solution to this issue. Third, Lo and MacKinlay (1990) and Chordia, Sarkar, et al. (2011) suggest that non-synchronous trading is not an explanation for the presence of Granger causality.

3.2. Preliminary Analysis

Unreported preliminary analyses use four lags of the returns of both indices and the panel approach as described below. There are three important results. First, the returns of the small-cap index do not Granger-cause the returns of the large-cap index. This is regularly reported in the literature. Second, the returns of the large-cap index Granger-cause the returns of the small-cap index. This result is not exceptional. Third, the estimated coefficient of the first lag of the large-cap index is statistically non-zero. The estimated coefficients of the three other large-cap lags are not statistically different from zero. Thus, we use a single-lag model. We note that Coccorese (2008, p. 562) and Chordia, Sarkar, et al. (2011, p. 724) use a single lag in the Granger causality test.

3.3. Building the Model

A conventional, one lag and one country, Granger model is written as

$$r_t^S = \alpha_0 + \alpha_1 r_{t-1}^S + \alpha_2 r_{t-1}^L + e_t \tag{7}$$

where r_t^S and r_t^L are the daily rates of return of the small-cap index and the large-cap index, respectively, and e_t is the error term. Variable r_{t-1}^S is a control variable—its purpose is to remove the influences of serial correlation in the dependent variable. Serial correlation is frequently observed in stock index returns. The variable of interest is r_{t-1}^L. Its effect is estimated after the influences of r_{t-1}^S are taken into account. It measures the degree that the information in the large-cap index causally influences the returns of the small-cap index. The estimated coefficient $\hat{\alpha}_2$ of variable r_{t-1}^L is called “Granger causality”.

Equation 7 represents a “single period” measure of Granger causality. A temporal dimension can be achieved by using a year indicator Y_t (=0–20) as an additional covariate. The Monday effect can be captured by including the dummy variable M_t which takes on a value of 1 if day t is a Monday, otherwise zero.

3.4. The Panel Model

Rather than using a country-by-country analysis (Gutierrez et al., 2009), we apply a single panel regression model incorporating all 17 countries. We do not force all countries to conform to the same set of estimated coefficients. Rather, we estimate a separate set of coefficients for each country within the framework of a single panel regression. We then finesse the "average" of the 17 estimated coefficients for each independent variable and their standard errors. The panel regression model employed is

$$\begin{aligned} r_{i,t}^{S} = {} & \sum_{i=1}^{17}\alpha_{0,i}D_i + \sum_{i=1}^{17}\beta_{0,i}D_iY_t + \sum_{i=1}^{17}\gamma_{0,i}D_iM_t + \sum_{i=1}^{17}\delta_{0,i}D_iM_tY_t \\ & + \sum_{i=1}^{17}\alpha_{1,i}D_ir_{i,t-1}^{S} + \sum_{i=1}^{17}\beta_{1,i}D_ir_{i,t-1}^{S}Y_t + \sum_{i=1}^{17}\gamma_{1,i}D_ir_{i,t-1}^{S}M_t + \sum_{i=1}^{17}\delta_{1,i}D_ir_{i,t-1}^{S}M_tY_t \\ & + \sum_{i=1}^{17}\alpha_{2,i}D_ir_{i,t-1}^{L} + \sum_{i=1}^{17}\beta_{2,i}D_ir_{i,t-1}^{L}Y_t + \sum_{i=1}^{17}\gamma_{2,i}D_ir_{i,t-1}^{L}M_t + \sum_{i=1}^{17}\delta_{2,i}D_ir_{i,t-1}^{L}M_tY_t + e_{i,t} \end{aligned} \tag{8}$$

where the constant is suppressed and subscript i represents the countries (=1, …, 17) and D_i represents the 0,1 dummy variables—one for each country. The model is estimated by the panel GLS method using cross-section weights and panel corrected standard errors. This provides control for heteroscedasticity and contemporaneous correlation of the errors across countries. The lagged rates of return provide control for serial correlation. The average of the 17 coefficients for each independent variable is denoted with an "overbar." As an illustration, the average value of the constants is calculated as

$$\bar{\alpha}_0 = (1/17) \times \sum_{i=1}^{17}\alpha_{0,i} \tag{9}$$

The averages and their corresponding standard errors are calculated by the use of additional linear restriction tests within the panel regression.

The coefficients in the first row of Equation 8, i.e. those with a subscript of 0, measure the temporal effect and the Monday effect in the returns of the small-cap indices. The coefficients in the second row, i.e. those with a subscript of 1, are the control variables mandated by the Granger causality test. The estimated coefficients in row one and row two are reported without comment since they measure the effects of the control variables. The primary focus is on the four sets of coefficients in row three—those with a subscript of 2. Their common characteristic is the presence of the r_{t-1}^{L} variable. The very essence of the study is expressed by the line of best fit representation of the expected Granger causality.

$$E(\text{Granger Causality}) = \bar{\alpha}_2 + \bar{\beta}_2Y_t + \bar{\gamma}_2M_t + \bar{\delta}_2M_tY_t \tag{10}$$

This is the average partial effect of r_{t-1}^{L} on r_t^{S}. It characterizes the systematic way that the average Granger causality is influenced by Y_t, M_t and their interaction.

The mean value of each of the estimated coefficients of the 17 countries captures the average magnitude of Granger causality. The conventional interpretation is: (1) coefficient $\bar{\alpha}_2$ is the Granger causality on non-Mondays in 1990 (i.e. when Y_t=0), (2) coefficient $\bar{\beta}_2$ measures the temporal slope of the Granger causality on non-Mondays, (3) the Granger causality on Mondays in 1990 is given by $\bar{\alpha}_2 + \bar{\gamma}_2$, and (4) the temporal slope of the Granger causality on Mondays is given by $\bar{\beta}_2 + \bar{\delta}_2$. Empirical support for hypothesis H is found if: (1) $\hat{\bar{\alpha}}_2 > 0$ and $\hat{\bar{\beta}}_2 < 0$ and/or (2) $\hat{\bar{\gamma}}_2 > 0$ and $\hat{\bar{\delta}}_2 < 0$. To acknowledge the predictions of sign, it is necessary to use a one-sided test of statistical significance of each of these coefficients.

4. Results and Discussion

The panel regression results are presented in Table 2, where the reported p-values are one-sided. In 1990, the Granger causality on non-Mondays is significantly positive ($\hat{\bar{\alpha}}_2$=.1468, t=4.50, p<.001).

Table 2. Small Index Effects

Variable	Name of coefficient	Estimated coefficient	Standard error	t	p
Panel A: M_t and Y_t effects on $r^S_{i,t}$					
Constant	$\bar{\alpha}_0$	.0318	.0259	1.23	.110
Y_t	$\bar{\beta}_0$	−.0011	.0022	−.50	.307
M_t	$\bar{\gamma}_0$	−.1211	.0582	−2.08	.019
M_tY_t	$\bar{\delta}_0$	.0063	.0050	1.27	.103
Panel B: $r^S_{i,t-1}$ effects on $r^S_{i,t}$					
$r^S_{i,t-1}$	$\bar{\alpha}_1$	−.0553	.0373	−1.48	.069
$r^S_{i,t-1}Y_t$	$\bar{\beta}_1$	.0039	.0037	1.06	.144
$r^S_{i,t-1}M_t$	$\bar{\gamma}_1$	.1887	.0863	2.18	.014
$r^S_{i,t-1}M_tY_t$	$\bar{\delta}_1$	−.0065	.0085	−.77	.222
Panel C: $r^L_{i,t-1}$ effects on $r^S_{i,t}$					
$r^L_{i,t-1}$	$\bar{\alpha}_2$	.1468	.0326	4.50	<.001
$r^L_{i,t-1}Y_t$	$\bar{\beta}_2$	−.0069	.0033	−2.10	.018
$r^L_{i,t-1}M_t$	$\bar{\gamma}_2$	.1263	.0763	1.66	.049
$r^L_{i,t-1}M_tY_t$	$\bar{\delta}_2$	−.0136	.0076	−1.79	.037

Notes: The estimated coefficients reported are averages over the 17 countries, using the panel data regression

$$r^S_t = \alpha_0 + \alpha_1 r^S_{t-1} + \alpha_2 r^L_{t-1} + \beta_0 Y_t + \beta_1 r^S_{t-1} Y_t + \beta_2 r^L_{t-1} Y_t + \gamma_0 M_t + \gamma_1 r^S_{t-1} M_t + \gamma_2 r^L_{t-1} M_t + \delta_0 M_t Y_t + \delta_1 r^S_{t-1} M_t Y_t + \delta_2 r^L_{t-1} M_t Y_t + e_t$$

where r^S_t = daily rate of return of the small-cap index, r^L_t = the daily rate of return of the large-cap index, Y_t = the time index 0–20, and M_t = 1 if day t is a Monday, otherwise 0.

This is consistent with Axiom 1. This strong Granger causality declines at a statistically significant rate ($\hat{\bar{\beta}}_2 = -.0069$, $t = -2.10$, $p = .02$). These results support hypothesis H. The market efficiency of the small-cap index increases at a faster rate than the market efficiency of the large-cap index. Under Axiom 1, this implies convergence of market efficiency, i.e. a slowing down in the rate of improvement of market efficiency of the small-cap index. Thus, we confirm the US results of Fargher and Weigand (1998) for a further 16 international stock markets. In addition, we show that the rate of improvement in market efficiency decreases over time.

In 1990, there is modest statistical evidence that the Granger causality is greater on Mondays compared to non-Mondays ($\hat{\bar{\gamma}}_2 = .1263$, $t = 1.66$, $p = .05$). However, in economic terms, the difference is of greater practical importance. The estimated Granger causality on Mondays is $\hat{\bar{\alpha}}_2 + \hat{\bar{\gamma}}_2 = .2731$ (with $t = 3.96$ and $p < .001$ via an additional linear restrictions test). This is almost twice the size of the estimated coefficient on non-Mondays. This is consistent with the frequent observation that stock index returns are anomalous on Mondays. This Granger causality declines at a faster rate on Mondays compared to non-Mondays ($\hat{\bar{\delta}}_2 = -.0136$, $t = -1.79$, $p = .04$). The difference in the temporal slope is of economic importance. The slope on Mondays is almost three times the slope on non-Mondays ($\hat{\bar{\beta}}_2 + \hat{\bar{\delta}}_2 = -.0206$, $t = 2.99$, $p = .001$ via an additional linear restrictions test).

These results for Mondays provide additional support for hypothesis H. The relatively higher Granger causality on Mondays, compared to non-Mondays, and its relatively faster temporal decline indicates that the market efficiency of the small-cap indices increase over time at a decreasing rate. Thus, there is clear support for hypothesis H.

5. Robustness Tests

It has been suggested to us by two referees of the journal that our earlier focus on the mean results may mask unknown variation within the sample of 17 countries. The implication is that different conclusions may eventuate in a country-by-country analysis. Table 3 presents the estimates of the four Granger causality coefficients broken down by country (Panel A), together with selected descriptive statistics (Panel B). The per capita gross domestic product GDP is for the year 2004 in US dollars. The source is Heston, Summers, and Aten (2009).

The presence of between-country variation is observed. Consider, as an example, the estimated $\hat{\alpha}_{2,i}$ coefficients—the Granger causality in 1990 on non-Mondays. The estimated coefficient is negative for the USA (−.2666) and Japan (−.2507) and essentially zero for Korea (−.0212) and Finland (.0284). For the remaining 13 countries, the estimated coefficient ranges from .0400 (Holland) to .6014 (France). Similar variation is observed for the three other sets of estimated Granger causality coefficients ($\hat{\beta}_{2,i}$, $\hat{\gamma}_{2,i}$ and $\hat{\delta}_{2,i}$).

The Jarque–Bera tests of normality point to the fact that each of the four sets of cross country estimates is normally distributed at the 5% level of significance ($\hat{\delta}_{2,i}$ has the largest Jarque–Bera statistic of 5.71 with $p > .05$). There are two implications. First, the average results for the 17

Table 3. Estimated Granger Causality and GDP

Country	Non-Mondays		Mondays (marginal)		GDP
	Intercept	Slope	Intercept	Slope	
	$\hat{\alpha}_{2,i}$	$\hat{\beta}_{2,i}$	$\hat{\gamma}_{2,i}$	$\hat{\delta}_{2,i}$	
Panel A: Granger causality by country					
Australia	.1388	−.0097	.1095	−.0164	30240
Hong Kong	.0521	.0028	.1450	−.0058	32550
UK	.2059	−.0183	1.1770	−.0761	27032
Germany	.3963	−.0105	.3525	−.0958	29051
USA	−.2666	.0163	.0799	−.0074	39441
Holland	.0400	.0073	.3024	−.0386	31927
France	.6014	−.0526	−1.0015	.0566	27311
Japan	−.2507	.0178	−.3149	.0206	28341
Singapore	.1641	−.0105	.1856	−.0022	35424
Spain	.0873	−.0019	.3878	−.0246	24945
Italy	.4061	−.0381	−.1347	.0388	27142
Korea	−.0213	.0113	.0804	.0080	18597
Sweden	.1438	−.0086	.1661	−.0214	27174
Denmark	.2554	−.0090	.2933	−.0352	30468
Austria	.2600	−.0086	.3442	−.0344	31574
Finland	.0285	.0058	−.0405	.0042	26402
Ireland	.2550	−.0116	.0145	−.0020	31389
Panel B: Descriptive statistics					
Mean	.1468	−.0069	.1263	−.0136	29353
Maximum	.6014	.0178	1.1770	.0566	39441
Minimum	−.2667	−.0526	−1.0015	−.0958	18597
Standard Deviation	.2196	.0181	.4268	.0374	4546
Jarque–Bera statistic	.015	3.102	5.710	.392	.739
Jarque–Bera probability	.992	.212	.058	.822	.691

Notes: $\hat{\alpha}_{2,i}$ measures Granger causality on non-Mondays at the start of the data 1990.

$\hat{\beta}_{2,i}$ measures how Granger causality on non-Mondays changes over time. The difference made to these measures by Mondays are captured by $\hat{\gamma}_{2,i}$ and $\hat{\delta}_{2,i}$, respectively.

countries, reported earlier, have economic meaning even if there is variation in the sample. Second, simple correlation analysis is a suitable methodology to compare the relationships between the four sets of Granger causality (see below).

A possible explanation for the between-country variability may be found in differences in economic development. The level of market efficiency is inversely related to the level economic development (Keef et al. 2009). Another explanation may be found in the interrelationships between the four sets of Granger causality. Consider, for example, the Granger effect at the start of the data. The Granger causality on non-Mondays ($\hat{\alpha}_{2,i}$) may be related to the excess Granger causality on Mondays ($\hat{\gamma}_{2,i}$). Table 4 presents the correlation coefficient matrix for $\hat{\alpha}_{2,i}$, $\hat{\beta}_{2,i}$, $\hat{\gamma}_{2,i}$, and $\hat{\delta}_{2,i}$ together with GDP. This is based on the data presented in Table 3 (Panel A).

Strictly interpreted at the $p = .05$ critical level of statistical significance, the GDP of the country has no systematic influence on the four sets of Granger causality coefficients. The largest correlation in absolute value is that of $\hat{\alpha}_{2,i}$ with GDP ($|r| = .18$, $p = .47$). The lack of statistical significance is not unexpected. The samples are from highly developed countries. The constrained range in the level of GDP is the most likely explanation for the lack of statistical significance.

However, an insight into the cross-country variations of Granger causality is offered by the correlations of the Granger causality coefficients. Consider the Granger causality on non-Mondays. The estimated coefficients $\hat{\alpha}_{2,i}$ and $\hat{\beta}_{2,i}$ are negatively correlated ($r = -.92$, $p < .001$). The implication is that the greater the Granger causality at the start of the data in 1990, the faster the decline in the causality over the following years. This is strong country-by-country support for hypothesis H.

Now consider the Granger causality on Mondays. The estimated coefficients $\hat{\gamma}_{2,i}$ and $\hat{\delta}_{2,i}$ are referenced against the corresponding non-Monday estimates. These Monday coefficients are negatively correlated ($r = -.83$, $p < .001$). This shows that the greater the "excess Granger causality on Mondays" in 1990, the faster the "decline in excess Granger causality on Mondays" over the following years. This provides indirect support for hypothesis H. A more direct test would be to compare the actual Granger causality on Mondays at the start of the data ($\hat{\alpha}_{2,i} + \hat{\gamma}_{2,i}$) with the actual decline in the Granger causality on Mondays ($\hat{\beta}_{2,i} + \hat{\delta}_{2,i}$). These two new measures of Granger causality and its rate of decay are negatively correlated ($r = -.88$, $p < .001$). The implication is that the Mondays and non-Mondays conform to the same structural model relating the initial level of inefficiency and the way that it declines overtime.

The cross pairs of the estimated coefficients in the sets ($\hat{\alpha}_{2,i}$, $\hat{\beta}_{2,i}$) and ($\hat{\gamma}_{2,i}$, $\hat{\delta}_{2,i}$) are not significantly correlated. The highest correlation is between $\hat{\beta}_{2,i}$ and $\hat{\gamma}_{2,i}$ ($r = .29$, $p = .242$). The implication is clear. It confirms that Mondays share the same structural model with non-Mondays.

Table 4. Correlations of the Country-specific Granger Causality Coefficients

	$\hat{\alpha}_{2,i}$	$\hat{\beta}_{2,i}$	$\hat{\gamma}_{2,i}$	$\hat{\delta}_{2,i}$	$\hat{\alpha}_{2,i} + \hat{\gamma}_{2,i}$	$\hat{\beta}_{2,i} + \hat{\delta}_{2,i}$	GDP
$\hat{\alpha}_{2,i}$	1.00						
$\hat{\beta}_{2,i}$	−.92 (<.001)	1.00					
$\hat{\gamma}_{2,i}$	−.16 (.527)	.29 (.242)	1.00				
$\hat{\delta}_{2,i}$	−.01 (.971)	−.24 (.347)	−.83 (<.001)	1.00			
$\hat{\alpha}_{2,i} + \hat{\gamma}_{2,i}$	.34 (.164)	−.17 (.497)	.87 (<.001)	−.80 (<.001)	1.00		
$\hat{\beta}_{2,i} + \hat{\delta}_{2,i}$	−.45 (.045)	.25 (.327)	−.69 (<.001)	.88 (<.001)	−.88 (<.001)	1.00	
GDP	−.18 (.471)	.13 (.606)	.04 (.864)	−.11 (.672)	−.05 (.856)	−.05 (.862)	1.00

Notes: $\hat{\alpha}_{2,i} + \hat{\gamma}_{2,i}$ measures Granger causality on Mondays at the start of the data 1990.

$\hat{\beta}_{2,i} + \hat{\delta}_{2,i}$ measures how Granger causality on Mondays changes over time.

The estimated correlation coefficients are *t*-distributed with 15 degrees of freedom. The *p*-values for the null hypothesis of zero correlation appear within parentheses.

There are two primary conclusions relating to the examination of the observed country-by-country variation in Granger causality. First, this variation cannot be convincingly explained by between-country variation in GDP. This is not an unexpected result—the sample represents developed economies with a narrow range in economic development. Second, there is strong support for hypothesis H when the Granger causality is examined on a country-by-country basis.

A further robustness check relating to the possible presence of ARCH has been recommended by one of the referees. This matter can be addressed in two ways. If data with no missing values over time are available, then the regression coefficients can be estimated consistently based on an appropriate GARCH specification of the error variance. If there are missing values, as with non-trading days when using daily stock price data, regression coefficients can still be estimated consistently by the least squares method, with valid hypothesis tests if the coefficient standard errors are estimated consistently. The option available to us is the latter. The new one-sided *p*-values that are robust to arbitrary heteroscedasticity over time (including GARCH) for the Granger causality coefficients on non-Mondays are $p<.001$ and $p=.036$ for $\hat{\alpha}_2 = .1468$ and $\hat{\beta}_2 = -.0069$, respectively. The new one-sided *p*-values for the Granger causality coefficients for Mondays are $p<.001$ and $p=.017$ for $\hat{\alpha}_2+\hat{\gamma}_2 = .2731$ and $\hat{\beta}_2+\hat{\delta}_2 = -.0206$, respectively. These results confirm our conclusion that market efficiency of small-cap indices increases over time at a decreasing rate.

6. Conclusions

The study is based on a pair of stock indices from 17 highly developed countries. The conclusion is reached that market efficiency of small-cap indices increases over time at a decreasing rate. The study raises two issues. First, an interesting question is the degree that the results apply to less developed countries. Ceteris paribus, these countries are expected to provide stronger support for the hypothesis since they are experiencing rapid economic development. This implies that the level of market efficiency of their stock exchanges is increasing in a concomitant fashion. Second, researchers into stock market anomalies and/or market efficiency should take into account the degree that the magnitude of the anomaly (e.g. Marquering, Nisser, & Valla, 2006) and/or the level of market efficiency evolve over time.

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