# Short-Horizon Return Predictability in International Equity Markets

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**Abstract**

This study measures the degree of short-horizon return predictability of 50 international equity markets and examines how its variation is related to the indicators of equity market development. Two multiple-horizon variance ratio tests are employed to measure the degree of return predictability. We find evidence that return predictability is negatively correlated with publicly available indicators of equity market development. Our cross-sectional regression analysis shows that the per capita GDP, market turnover, investor protection, and absence of short selling restrictions are correlated with cross-market variations in return predictability.

JEL Classifications: G12, G14, G15

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## 1. Introduction

The predictability of stock returns has received considerable attention in finance. The literature provides mixed evidence regarding return predictability in international stock markets. The generally accepted view is that emerging equity markets show a higher degree of return predictability than developed ones (see, for example, Harvey, 1995; Bekaert and Harvey, 1995). In contrast to this view, a number of recent studies claim that stock returns in emerging markets appear to be less predictable than developed ones (see, for example, Al-Khazali, Ding, and Pyun, 2007; Griffin, Kelly, and Nardari, 2007). The literature also provides evidence that return predictability varies over time within a market. As noted in Gu and Finnerty (2002), there has been a secular decline of index return autocorrelation in the U.S. over the last century, with a tendency for negative (positive) autocorrelation in the period of high (low) volatility.

There is also considerable debate over the sources of return autocorrelation. One strand of the literature interprets evidence of predictability as a manifestation of informational inefficiency due to behavioral biases (e.g., Daniel and Titman, 1999; Barberis, Shleifer, and Vishny, 1998). A large body of recent literature suggests that the presence of return predictability can be compatible with rational asset pricing models and does not necessarily imply informational inefficiency (see Berk, Green, and Naik, 1999; Johnson, 2002; Sagi and Seasholes, 2007; Liu and Zhang, 2008). As discussed in the next section, non-zero return autocorrelations can be associated with market frictions or time-varying expected returns under market rationality. This body of literature suggests a link between cross-market variation in return autocorrelation and market characteristics that represent underlying frictions.

Given this backdrop, this study makes the following contributions. The first aim of the paper is to test the hypothesis that daily stock returns are purely unpredictable, using stock price indices from 1998 to 2007 for 50 equity markets that are at various stages of development. To measure the degree of return predictability, we employ two multiple-horizon variance ratio tests, both of which are based on non-parametric methods. One is the wild bootstrap test of Kim (2006) and the other a sign test proposed by Kim and Shamsuddin (2008). These details are in Section 3.

Second, this paper evaluates the correlation between the measures of return predictability and equity market development rankings by the Financial Times Stock Exchange (FTSE), Standard & Poor's (S&P), and the World Bank. The World Bank grades equity markets on financial indicators of development, whereas the FTSE and S&P rank equity markets on the degree of investability, which in turn is determined by financial as well as regulatory quality indicators of development. Third, to further examine cross-market variation in stock return predictability, this study conducts multiple regression analysis to evaluate the link between the measures of return autocorrelation and market characteristics, such as market size, turnover, financial disclosure, investor protection, and capital market openness, among others.

Overall, our findings are compatible with the common belief that stock returns of emerging markets are more predictable than those of developed ones. We also find a significant inverse relation between return predictability and the level of equity market development, thus establishing a bridge between the academic literature on predictability and market rankings by commercial equity index creators and international agencies. Our cross-sectional regression analysis also shows that market turnover, investor protection, and absence of short selling restrictions are negatively related to return autocorrelation.

## 2. Short-horizon return predictability

### *2.1. A brief review of past studies*

If a stock price follows a random walk (or martingale) process, the current price is the best predictor of the future price, and future returns are purely unpredictable from their past values. In general, the early literature on return predictability (Fama, 1965, 1970) finds no evidence of autocorrelation in stock returns, providing overwhelming support for the random walk hypothesis. Following the seminal studies, a large body of literature since the mid-1980s provides evidence in favor of return predictability, especially for small firms, national stock indices, and emerging equity markets. For example, Jegadeesh and Titman (1993) report momentum effects, and DeBondt and Thaler (1985) find a long-run return reversal effect. The momentum effect (reversal effect) is sometimes interpreted as a manifestation of investors' underreaction (overreaction) to new information due to cognitive bias. Others attempt to explain short-horizon return reversals in terms of lagged order imbalances and belief reversion (e.g., Subrahmanyam, 2005).

There are three possible explanations for stock-index autocorrelation that do not require the presumption of market irrationality. First, autocorrelations in short-horizon index returns can be attributed to market frictions in the form of non-synchronous trading (more precisely, non-synchronous recording of stock prices). A national stock index represents a mix of stale and contemporaneous stock prices due to non-synchronous trading of the stocks in the index (Lo and MacKinlay, 1990). The non-synchronous trading effect is more severe for a portfolio dominated by thinly traded stocks such as small firm stocks (Atchison, Butler, and Simonds, 1987).

Second, common information can be transmitted into stocks on a non-synchronous basis due to other forms of market friction such as information and trading costs. In Black (1986), there are two groups of traders in the market: liquidity traders (a demander or supplier of immediacy) and informed traders. The former group trades more frequently than the latter and will trade if the prevailing price sufficiently deviates from its equilibrium value to yield arbitrage profits, net of transaction costs.[1] Thus, information could be incorporated into the prices of some stocks with a delay (see Hou and Moskowitz, 2005), which can induce autocorrelation in index returns. This line of argument is supported by the finding that, on average, small stocks require more time to incorporate new information into prices than large stocks; and autocorrelation is positive and stronger for portfolios of small capitalization stocks (Lo and MacKinlay, 1988). Indeed, return autocorrelation for a national stock index can be driven by a lead-lag relation running from large capitalization stocks to small ones, according to Lo and MacKinlay (1990).

Third, short-horizon stock returns can be autocorrelated even in a frictionless rational market due to time-varying economic risk premiums. Berk, Green, and Naik (1999) put forward a model where a firm's assets and growth opportunities follow a predictable pattern over its life cycle, which in turn results in momentum in stock returns. Johnson

[1] In the presence of market frictions, trading activity can also lead to stock price changes. For example, Chordia, Roll, and Subrahmanyam (2002) observe that returns are partially predictable from lagged order imbalances. A strong relation between market maker inventories and future stock returns is reported by Hendershott and Seasholes (2007).

(2002) also explains momentum effects within a rational asset pricing model where stock prices nonlinearly depend on time-varying growth rates. More specifically, return autocorrelation is positive for a firm for which value (in logarithm) is convex in its growth rates. Sagi and Seasholes (2007) extend Johnson's work by viewing a firm as a portfolio of assets comprised of revenues, costs, growth options, and shutdown options. They demonstrate that return autocorrelation is the outcome of the way in which a firm combines its asset portfolio. Any change in a firm's asset portfolio can lead to a change in the firm's risk characteristics, which in turn change return autocorrelation. Thus, return autocorrelation could vary over the life cycle of a firm.

Although the empirical literature on return predictability is overrepresented by studies for the U.S. market over the past two decades, a number of studies have appeared that consider the return predictability in international equity markets. Harvey (1995) observes that emerging markets have a higher first-order return autocorrelation than developed markets. The first-order autocorrelation is found to be negatively associated with market capitalization, trading volume, and the number of companies in the index and positively linked with the concentration ratio (percentage of capitalization of the top ten firms). However, Harvey's cross-sectional regression results should be viewed with caution as they include up to 11 independent variables for a maximum sample of 22 markets.

Recent studies such as Al-Khazali, Ding, and Pyun (2007) argue that the previous finding of stock return predictability could be attributed to thin trading. They interpret thin trading as a manifestation of measurement error and attempt to correct for potential biases by adopting the data filtering process proposed by Miller, Muthuswamy, and

Whaley (1994). The approach essentially removes first-order autocorrelation from the return series by an AR(1) model and then searches for evidence of return predictability in the residual return series. Any study based on the residual series is likely to draw a conclusion in support of no return predictability because the residual series is created by removing autocorrelations from the observed return series. Indeed, unlike earlier studies, Al-Khazali, Ding, and Pyun are unable to reject the random walk hypothesis for Middle Eastern and North African (MENA) markets. Using return residuals from an AR(1) model, Lim and Brooks (2007) also find that developed markets (such as the U.S. and Australian equity markets) are less efficient than emerging markets, including Thailand, Jordon, Malaysia, and Egypt. In contrast to these studies, we argue that non-synchronous or thin trading cannot be dismissed simply as a reflection of measurement error in a national stock index (see Lo and MacKinlay, 1990, p.205), and we use the raw return data to measure the degree of return predictability.[2] Even using the raw return data, Griffin, Kelly, and Nardari (2007) provide a counterintuitive finding that emerging equity markets are at least as efficient as their developed counterparts.

*2.2. Contribution of this study*

Our study differs from previous research in three important ways. First, we measure and test the degree of return predictability over a set of holding periods using two non-parametric multiple horizon variance ratio tests: one based on a wild bootstrap and the other on signs. According to Kim (2006) and Kim and Shamsuddin (2008), these tests have superior size and power properties in small samples compared to conventional multiple horizon variance ratio tests. Second, Harvey (1995) and Griffin, Kelly, and

[2] Although our study presents the results from raw return data, the implications of thin trading adjustments are also explored for 27 emerging markets in our sample. We find that nearly all emerging markets are predictable with thin trading adjustments. This result is unrealistic and seems to confirm our suspicion that time series filtering results in a failure to reject a false null hypothesis.

Nardari (2007), among others, use per capita income to divide countries into developed and emerging markets. Although per capita income is positively associated with the level of equity market development, this relation is far from perfect. Thus, we employ the market classification standard proposed by FTSE, S&P and the World Bank to classify markets on an ordinal scale of development. We then attempt to uncover the correlation between return predictability and the ordinal scale of equity market development. Finally, one of the problems in regression modeling of cross-market variation in return autocorrelation is that there are too many potential explanatory variables with overlapping information content. Given the lack of a well-structured theoretical model in this area, some studies adopt a data mining approach to reduce the number of explanatory variables. In contrast, the current study considers only those factors that represent aspects of market frictions and the general indicators of market development. These factors are further elaborated in Section 4.

## 3. Measuring short-horizon return predictability

### *3.1. Multiple-horizon variance ratio tests*

We use two alternative multiple-horizon variance ratio (*M-VR*) tests for asset return predictability. For simplicity, only brief and intuitive descriptions of these tests are given here. Let $V_k$ be the variance of the stock return over holding period $k$. The variance ratio for holding period $k$ is defined as $VR(k) \equiv V_k / kV_1$. It can be shown that $VR(k)$ is equal to one plus a weighted sum of return autocorrelations up to lag $k$-1, with positive and declining weights. If stock returns are purely random and unpredictable, $VR(k) = 1$ for all $k$. On this basis, Griffin, Kelly, and Nardari (2007) use $|VR(k) - 1|$ as a measure of return predictability, where |.| indicates the absolute value. However, this measure cannot provide a single indicator of predictability over a set of multiple holding periods, and it ignores sampling variability in the estimation of return predictability.

As an alternative measure over a set of holding periods $k_i$ ($i$ = 1, …, $l$), we use a modified version of the *M-VR* test statistic developed by Chow and Denning (1993) of the following form:

$$M\text{-}VR(r;k_1,\dots,k_l) = \max_{1\le i\le l} \left| M(r;k_i) \right| \quad , \tag{1}$$

where $M(r;k_i)$ is the test statistic for $H_0$: $VR(k_i) = 1$ for all $k_i$ as proposed by Lo and MacKinlay (1988), and $r$ denotes the stock return. While Chow and Denning (1993) show that the *M-VR* statistic given in (1) follows the studentized maximum modulus distribution in large samples, its sampling variability is completely unknown in small samples. In this paper, we estimate the standard error of (1) using the wild bootstrap procedure of Kim (2006). The wild bootstrap also provides a *p*-value for statistical inference.

A potential problem associated with the *M-VR* statistic is that it can be influenced by outliers in stock returns. To conduct a statistical test and obtain a measure of predictability that is robust to the presence of outliers, we also use a sign test version of (1) proposed by Kim and Shamsuddin (2008), which is denoted as *M-VR-S.* Since it is an exact test, the sampling variability of the *M-VR-S* test is constant, for a given sample size and a set of holding periods. The *p*-value of the test can be calculated from the exact sampling distribution, which can be obtained by conducting simulation.

### *3.2. Data and variance ratio test results*

The two variance ratio tests are applied to daily stock index returns from January 1, 1998 to December 31, 2007. This period is chosen to avoid the times of international equity market turbulence, such as the peak of the 1997 Asian financial crisis and the international fallout from the 2008 sub-prime lending crisis. We are interested in return predictability and its correlation with other market and economic factors during normal times. However, the sensitivity of the variance ratio test results to the inclusion of financial crisis periods (1997 and 2008) in the sample is also examined. Our sample includes 50 equity markets. From the investable universe of the FTSE, we select 23 developed, six advanced emerging, and 17 secondary emerging stock markets, which represent about 98% of the total capitalization of the world's investable markets. In addition, four new emerging markets on FTSE's watch list for possible future inclusion into investable markets are also considered. The FTSE's investable universe includes 28 out of the 29 investable markets covered by the S&P 1200 Global Index.[3]

Market capitalization-weighted price indices denominated in local currencies are used in this study. The return series is calculated as 100 times the first difference of the logarithmic price index, obtained from Datastream. The details of the data sources, descriptive statistics, and variance ratio test results for the period January 1, 1998 to December 31, 2007 can be obtained on request. The distribution of stock returns is far from normal for all cases, with negative skewness and substantial excess kurtosis. In general, the developed markets provide much lower local currency-denominated returns with modest standard deviations than advanced and secondary emerging markets. The finding holds even when returns are denominated in US dollars. The two multiple-

[3]See Standard & Poor's (2008a). The S&P investable market not covered by the FTSE is Luxembourg, which is not examined in this study.

horizon *VR* tests presented above are conducted with holding periods ($k_i$'s) 2, 5, 10, 20, and 40, which are popular values for the variance ratio test on daily returns. For all markets, the random walk hypothesis is rejected if the *p*-value is less than 0.10, at the 10% level of significance. According to the tests, 11 of the 23 developed stock markets are found to be predictable at the 10% level, and so are four of the six advanced emerging markets. For secondary emerging markets, the *M-VR* test (*M-VR-S* test) finds that 13 (14) out of the 17 markets are found to be predictable. All of the non-investable emerging markets show evidence of return predictability based on both test statistics.

Next, the sensitivity of the variance ratio test results to financial crisis is investigated by including the periods of the Asian financial crisis (1997) and the sub-prime lending crisis (2008) in the sample. Figure 1 summarizes the key findings for samples with and without crisis periods. In general, the incidence of return predictability is inversely related to the level of equity market development, as measured by FTSE.[4] This general finding is invariant to the test adopted or the sample period used. Both tests give similar results for each market category in the 1998-2007 sample. However, for the 1997-2008 sample, the *M-VR-S* test yields a higher incidence of return predictability compared to the *M-VR* test for all but the non-investable markets.

The source of the divergence between the two test results becomes apparent in Figure 2, which displays time variation in return predictability for the overlapping rolling sample of a two-year window over 1997-2008. Although a significant number of the equity markets in our sample are found to be predictable, we do find evidence of time variation in return predictability. Both tests suggest that, in general, the incidence of

[4] The detailed *M-VR* and *M-VR-S* test results for the 1997-2008 sample are available from the authors.

return predictability has decreased over the whole sample span. According to the *M-VR* test, around 40% of all markets in our sample are found to be predictable during the initial sample window of 1997-1998, temporarily increases to 56% in 1998-1999, and then gradually decreases over time and reaches around 16% in the last sample window, 2007-2008. The *M-VR-S* test also shows a decline in the proportion of markets with significant non-zero autocorrelations, from 72% to 42% over 1997-1998, but with a greater degree of fluctuation. Although the figure shows that the discrepancy between the two test results becomes greater around a financial crisis (at both ends of our sample), the overall declining trend in return predictability is obvious.

**<INSERT TABLE 1>**
**<INSERT FIGURE 1>**
**<INSERT FIGURE 2>**

## 4. Return predictability and market characteristics

In this section, we examine how return predictability is correlated with publicly available market rankings, and we conduct a cross-sectional regression analysis to examine the relation between return predictability and market characteristics.

### *4.1. Link between return predictability and market ranking*

We examine the correlation between our measures of return predictability (*M-VR* and *M-VR-S* statistics) and the equity market rankings. The World Bank ranks markets based on financial indicators such as relative market capitalization, the number of listed firms, market turnover, volume of trade, the probability of earnings manipulation, the second and third moments of the distribution of stock returns, proxies for trading cost, and the information content in stock prices (World Bank, 2008). The FTSE employs a set of mandatory criteria for inclusion on its list of investable countries; and then further classifies the countries into developed, advanced emerging, and secondary emerging markets. The FTSE not only looks at the broad financial indicators but also at regulatory quality indicators and institutional factors conducive to the free flow of international capital and repatriation of returns. Standard and Poor's uses similar criteria. The country classification criteria used by FTSE and S&P can be found in FTSE (2008) and Standard and Poor's (2008b), respectively.

Table 1 presents two alternative non-parametric correlation coefficients that are suitable for evaluating the association between market predictability and equity market ranking. The market rankings are defined in the notes below the table heading. A higher market score refers to a lower level of market development, and a higher value of the test statistics implies a higher degree of return predictability. All correlation coefficients are highly significant with the expected positive sign, implying that the level of equity market development is inversely related to the degree of return predictability.

**<INSERT TABLE 1>**

*4.2. Cross-sectional regression analysis*

In the absence of an accepted theoretical model in the literature, we select indicators of equity market development as well as some environmental factors to guide our analysis. The overall quality of the market is approximated by relative market capitalization, liquidity, and restrictions on short selling. As a proxy for liquidity, market turnover (the ratio of the volume of trade to market capitalization) is used. In addition, we include per capita GDP as an environmental factor, as it is associated with many attributes of equity markets that are unobserved or difficult to measure. Environmental factors, such as capital market openness and the quality of governance, are also considered as they are associated with an investor's ability to respond to new information. It has been argued that a good financial disclosure regime is essential for the timely availability of information and to improve the value-relevance of accounting information.[5] However, many developed equity markets with apparent good disclosure practices have been subject to numerous incidents of distortion in financial statements. Thus, as a supplementary variable, the public enforcement index is also used. This is an indicator of criminal sanctions in the event that a company misleads investors. The variable definitions and data sources are provided in the notes for Table 2.

Although not reported in detail, we have evaluated the bivariate correlation coefficients of the variables involved. It shows that the *M-VR* statistic has a statistically significant negative correlation with the per capita GDP (in logarithm), equity market turnover, dummy variable for no short selling restrictions, capital market openness, and rule of law. The *M-VR-S* statistic has an expected significant inverse correlation with the per capita GDP (in logarithm), equity market turnover, dummy variable for no short selling restrictions, overall governance quality, and four dimensions of governance quality: voice and accountability, government effectiveness, regulatory quality, and rule of law. Thus, the correlation results for the *M-VR-S* statistic points towards more relevance of good governance for quick return adjustments. None of the findings is sensitive to the imputation of missing values, which is evident by comparing the upper triangle of the correlation matrix to the lower triangle.

The results for the five alternative specifications of the regression model are in Table 2. Panel A presents the weighted least squares results for the *M-VR*, where the weight is the reciprocal of the wild bootstrap standard error of *M-VR*. The first specification

[5] Indeed, DeFusco, Mishra, and Raghunandan (forthcoming 2009) observe that following the implementation of the Regulation Fair Disclosure in the US in 2000, the informational efficiency of US stock prices has improved.

includes an environmental variable (the logarithm of per capita GDP) and equity market turnover. The results show that return predictability is inversely correlated with turnover and logarithm of per capita GDP.  This finding is insensitive to the inclusion of additional regressors in the model.  After controlling for the effects of turnover and per capita GDP, relative market capitalization turns out to be statistically insignificant. This could be attributed to observed collinearity between the logarithm of per capita GDP and the ratio of market capitalization to GDP. The third specification includes financial disclosure requirements and public enforcement indices. The degree of return predictability is invariant to the financial disclosure variable but correlates negatively with the level of public enforcement of securities regulations. The former result is puzzling, as it shows that financial disclosure exerts no influence, whereas the latter finding is compatible with the emerging consensus in regulatory circles that the possibility of criminal sanctions against company directors in the event that they commit fraud or mislead investors is the most effective tool to protect investors. Many of the emerging markets in our sample have stringent financial disclosure requirements, but they are prone to market frictions due to a lack of securities-regulation enforcement.

Our next specification of the regression model includes a dummy variable for no short selling restrictions and an index of capital-market openness. The results suggest that return predictability is less prevalent in markets with no short selling restrictions but invariant to the extent of capital-market openness. Our results for market openness are not consistent with conventional wisdom. The free flow of international capital allows domestic residents to invest in foreign stocks and foreigners to invest in domestic stocks, which can foster international arbitrageurs to exploit potential mispricing in equity markets. However, the effect of capital market openness is difficult to quantify, as it is undertaken at discrete time intervals and has a blunt, sluggish influence on almost all sectors or markets of an economy. The effect of capital-market openness could be properly identified in a study of long-horizon return predictability with a longer sample. Finally, we look at the relation between the qualities of governance (measured on a scale of +2.5 to -2.5) and return predictability. There are six dimensions of the qualities of governance: control of corruption, rule of law, regulatory quality, government effectiveness, political stability, and voice and accountability. Due to extremely high multicollinearity among the variables, we use their average value as a regressor to represent the overall quality of governance. This variable turns out to be statistically insignificant in the regression. Panel B of Table 2 presents the ordinary least squares results using the *M-VR-S* statistic as the dependent variable.[6] In general, the results are similar, but the equations with *M-VR-S* statistics have lower values of $R^2$ than the *M-VR* equations.

To examine the sensitivity of the regression results to the imputation of missing values, we re-estimate all models by removing missing values from the data set (the results are not tabulated). The results for the equations with the *M-VR* statistic as the dependent variable do not show a great deal of sensitivity. In the equations for the *M-VR-S* statistics, the coefficient of the no short selling dummy is no longer significant. Other coefficients show a reasonable degree of tolerance to the listwise deletion of missing observations.

**<INSERT TABLE 2>**

## 5. Conclusion

[6] As mentioned before, the *M-VR-S* statistic follows the exact distribution with the same sampling variability. For this reason, weighted least squares estimation is not conducted in this case.

The issue of stock return predictability has received substantial attention in both academic and industrial circles. The main aim of this study is to measure return predictability in 50 international stock markets and examine how it is related to market and environmental factors. Applying two alternative nonparametric multiple-horizon variance ratio (wild bootstrap and sign) tests to the entire sample from 1998 to 2007, we find that 48% of developed, 67% of advanced emerging, 76% of secondary emerging, and all non-investable markets exhibit statistically significant return autocorrelations. We also find that return predictability is inversely related to equity market development, which is evident from the close link between our measures of short-horizon return predictability and the market-development rankings. Employing the rolling window of two years, we observe that the degree of return predictability declines over time. For example, the wild bootstrap test shows that over the initial sample window of 1998-1999, around 56% of all markets are inefficient. The percentage gradually decreases over time and reaches around 16% in the last window in 2006-2007. The joint sign test shows a less pronounced decline in return predictability over this sample span.

The cross-sectional regression results show that the per capita GDP, market turnover, public enforcement of securities regulations, and absence of short selling restrictions are inversely correlated with return predictability. Previous studies typically support the notion that market turnover reduces return predictability. For example, using intraday NYSE data, Chordia, Roll, and Subrahmanyam (2008) observe that return predictability diminishes significantly during more liquid regimes. The public enforcement of securities regulations has emerged as a crucial issue in regulatory and corporate circles over the past decade due to a number of high-profile corporate scandals (see Johnson, Boone, Breach, and Friedman, 2000). Our results suggest that criminal sanctions can be an effective tool to deter company directors from manipulating accounting numbers and misleading market participants. Though there is a negative bivariate correlation between governance quality and return predictability, no statistically significant relation exists between the two variables within the multiple regression model. The latter is possibly attributed to the high degree of collinearity between governance quality and logarithm of per capita GDP.

This study provides novel evidence that the incidence of return predictability has decreased over time in international equity markets, indicating a decline in the extent of market frictions. The factors related to return predictability are examined to gain insights about how market frictions and environmental factors can influence return predictability. Unlike previous studies, this evidence is drawn from two variance ratio test statistics with superior small sample properties that are capable of evaluating return predictability over multiple investment horizons. The findings of this paper could be of interest to investors willing to exploit apparent return predictability, as well as to stock exchanges and regulators who are keen to reduce market frictions.

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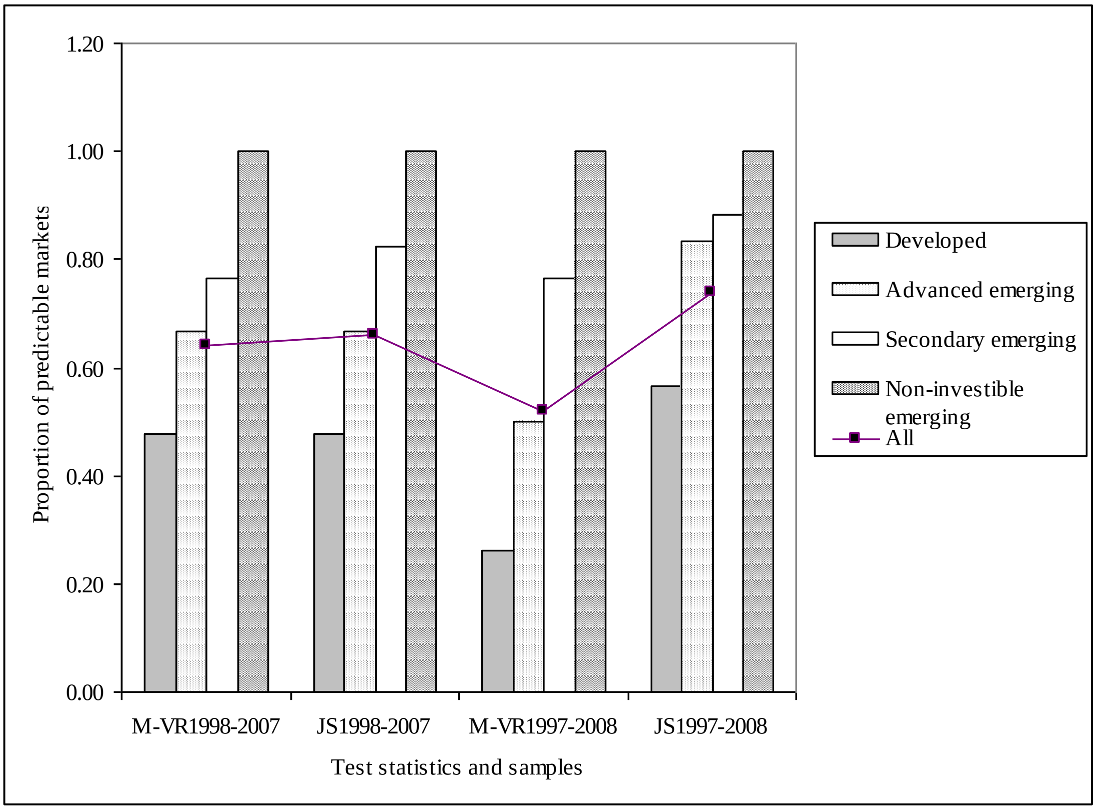


Figure 1

**Summary of multiple-horizon variance ratio (M-VR) and joint sign (M-VR-S) tests for samples with (1997-2008) and without abnormal periods (1998-2007)**

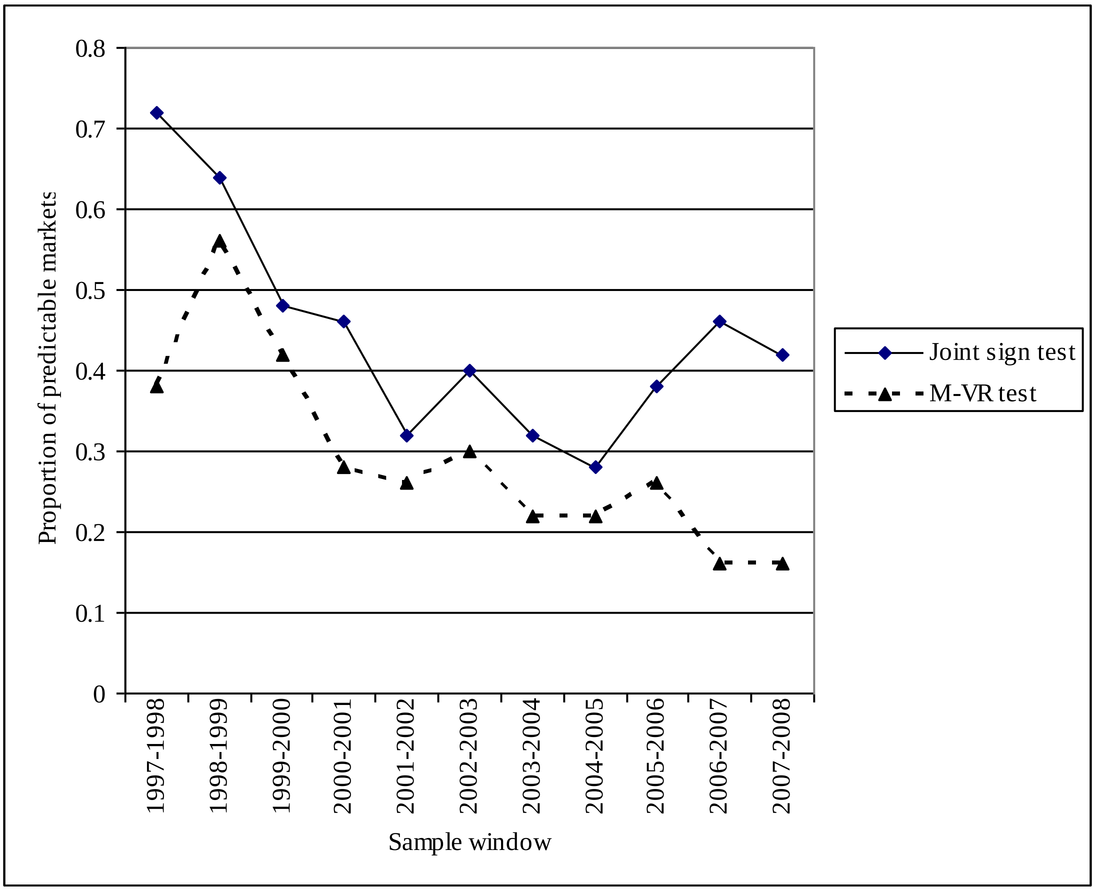


Figure 2

**Time variation in return predictability, 1997-2008**

Table 1

**Non-parametric correlation coefficient between equity market predictability measures and equity market ranking, January 1, 1998 to December 31, 2007**

For the FTSE market classification, we assign the following ordinal values: 1= developed, 2 = advanced emerging, 3 = secondary emerging, and 4 = non-investable market. For the Standard & Poor's market classification, a value of 1 is assigned if stocks from the market are included in the S&P Global 1200 index (investable markets) and a value of 2 otherwise (non-investable markets). The World Bank assigns an ordinal value of 1 to the most developed market, 2 to the second most developed market, and so on (see World Bank, 2008).

| | | Multiple-horizon variance ratio (M-VR)* | Joint sign statistic (M-VR-S)* |
|---|---|---|---|
| Kendall's tau_b | World Bank market ranking | 0.353 | 0.341 |
| | FTSE market ranking | 0.367 | 0.439 |
| | S&P market ranking | 0.285 | 0.304 |
| Spearman's rho | World Bank market ranking | 0.547 | 0.488 |
| | FTSE market ranking | 0.459 | 0.548 |
| | S&P market ranking | 0.346 | 0.369 |

*All correlations are statistically significant at 0.05 level (2-tailed).

Table 2

**Regressions of predictability measures on cross-country characteristics (complete data)**

The per capita GDP (in 2000 US dollars), ratio of market capitalization to GDP, and turnover are from *World Development Indicators*. The average values of these variables over 1998-2007 are used. The financial disclosure requirements and public enforcement indexes lie between 0 (worst possible securities regulations) and 1 (best possible securities regulations) and are from La Porta, Lopez-de-Silanes, and Shleifer (2006). The data are from http://www.economics.harvard.edu/faculty/shleifer/data_set. The dummy variable for no short selling restrictions is from Bris, Goetzmann, and Zhu (2007). The capital market openness is the average value over 2000-2005 of "International Capital Market Controls (column 4E)" as reported in Fraser Institute (2007). The six dimensions of the quality of governance are from www.worldbank.org/wbi/governance/. These indicators are compiled by Kaufmann, Kraay, and Mastruzzi (2008) and can take a value between +2.5 and -2.5. A higher value represents better governance outcome. The average values of the indicators over 1998-2007 are used. Missing observations are replaced with the imputed values from the expectation-maximization (EM) algorithm available in SPSS. The EM algorithm is based on the seminal work of Dempster, Laird, and Rubin (1977)..The sample size is 50.

*Panel A: Weighted least squares results for the multiple-horizon variance ratio (M-VR)*, with the weights as the reciprocal of the wild bootstrap standard error of *M-VR*.

| | Coefficients | *p*-value | Coefficients | *p*-value | Coefficients | *p*-value | Coefficients | *p*-value | Coefficients | *p*-value |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Weighted least squares results for the multiple-horizon variance ratio (M-VR)* | | | | | | | | | | |
| Constant | 7.499 | 0.000 | 7.234 | 0.000 | 9.399 | 0.000 | 7.269 | 0.001 | 9.270 | 0.031 |
| Log (per capita GDP) | -0.395 | 0.019 | -0.347 | 0.081 | -0.528 | 0.008 | -0.113 | 0.071 | -0.347 | 0.098 |
| Turnover | -0.013 | 0.000 | -0.013 | 0.000 | -0.015 | 0.000 | -0.014 | 0.000 | -0.014 | 0.000 |
| Capitalization/GDP | | | -0.002 | 0.389 | -0.001 | 0.818 | 0.001 | 0.814 | 0.001 | 0.819 |
| Financial disclosure | | | | | 1.210 | 0.310 | 0.936 | 0.430 | 0.740 | 0.549 |
| Public enforcement | | | | | -2.525 | 0.003 | -2.244 | 0.009 | -2.120 | 0.015 |
| Short selling dummy | | | | | | | -0.903 | 0.108 | -0.878 | 0.097 |
| Capital market openness | | | | | | | -0.208 | 0.257 | -0.237 | 0.178 |
| Governance quality | | | | | | | | | 0.440 | 0.5641 |
| R-squared | 0.289 | | 0.295 | | 0.349 | | 0.426 | | 0.433 | |
| Prob(F-statistic) | 0.000 | | 0.001 | | 0.002 | | 0.001 | | 0.002 | |
| *Panel B: Ordinary least squares results for the joint sign test statistic (M-VR-S)* | | | | | | | | | | |
| Constant | 15.536 | 0.001 | 15.706 | 0.002 | 17.735 | 0.006 | 14.727 | 0.030 | 15.961 | 0.042 |
| Log(Per capita GDP) | -1.103 | 0.010 | -1.135 | 0.032 | -1.321 | 0.033 | -1.227 | 0.028 | -1.370 | 0.043 |
| Turnover | -0.018 | 0.002 | -0.018 | 0.002 | -0.020 | 0.002 | -0.018 | 0.001 | -0.018 | 0.001 |
| Capitalization/GDP | | | 0.002 | 0.851 | 0.003 | 0.796 | 0.000 | 0.999 | 0.000 | 0.998 |
| Financial disclosure | | | | | 1.908 | 0.338 | 4.294 | 0.222 | 4.158 | 0.249 |
| Public enforcement | | | | | -2.866 | 0.054 | -3.600 | 0.048 | -3.506 | 0.059 |
| Short selling dummy | | | | | | | -2.483 | 0.086 | -2.471 | 0.090 |
| Capital market openness | | | | | | | 0.396 | 0.587 | 0.377 | 0.619 |
| Governance quality | | | | | | | | | 0.278 | 0.7948 |
| R-squared | 0.254 | | 0.254 | | 0.273 | | 0.346 | | 0.347 | |
| Prob(F-statistic) | 0.001 | | 0.003 | | 0.013 | | 0.009 | | 0.017 | |