An Empirical Analysis of Emerging Stock Markets of Europe

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This paper examines several aspects of the seven stock markets in Europe classified by the International Finance Corporation (IFC) as emerging markets. Specifically, we investigate correlations among the European emerging markets as well the U.S. and U.K. equity markets. In addition, we test for market efficiency and autocorrelation. Using weekly stock market data from the IFC, our findings indicate the greatest potential diversification benefits from a portfolio containing equities from Slovakia, Turkey, and the U.S. Further, we find that returns for Greece, Slovakia, and Turkey are unstable over time. Based on our results, we conclude that European emerging markets overall are unpredictable. Finally, our results show evidence of autocorrelation in European emerging markets.

Introduction

The demise of communism in Russia and Eastern Europe has led to increased opportunities for investors seeking greater potential returns and portfolio diversification. There is an important political context in which all of this occurred: the fall of communism and subsequent rise of populism, liberalization, modernization, and privatization have resulted in a more competitive economic landscape. This new political landscape also has opened stock markets to foreign investors, thus attracting much needed foreign capital for economic development.

Poland and Czechoslovakia were the first Eastern Bloc countries to initiate economic reforms. Other countries soon followed suit. The International Finance Corporation (IFC) now classifies seven countries in Europe as *emerging*: the Czech Republic, Poland, Russia, Hungary, Greece, Slovakia, and Turkey. The IFC defines an emerging stock market as any stock market located in a developing country, as

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defined by the World Bank's GNP per capita criterion for a developing country. In addition, the IFC considers size (as measured by market capitation) and liquidity (as measured by turnover) of a market in classifying that market as emerging and in deciding whether to include the country's securities in its emerging market data base (EMDB).

Emerging markets, in general, have gained the attention of investors, researchers, and policy makers in the last ten to fifteen years because of several factors. Perhaps the leading factor is their sound performance over the period, with yields in some markets far exceeding those of developed markets. Given the current international status and interest in emerging stock markets, the focus of this study is the stability, predictability, and volatility (including the persistence of volatility and time-varying risk premium) in the seven European emerging stock markets. Several papers have focused exclusively on developed stock markets and a few emerging markets in Asia, Europe, and Latin America. The primary focus of this study is the seven emerging markets of Europe. This study specifically examines whether these markets provide an avenue for investors seeking diversification and investors' potential returns over time to the changing risk patterns in these equity markets.

There is substantial diversity among the world's emerging markets in terms of infrastructure, market size, and liquidity. Some investors believe that emerging markets in Eastern Europe have greater growth potential over the next decade compared to the emerging markets of Asia and Latin America. European emerging markets may be viewed by investors as better quality than what is available in Asia or Latin America because the infrastructure and regulations of Eastern Europe are closer to that of developed markets. Furthermore, the high education levels in Eastern Europe, combined with lower salary levels compared to the developed world, make direct foreign investments and outsourcing production favorable.

According to International Monetary Funds (IMF), emerging market stocks currently represent approximately 10.4 percent of the capitalization of the world's equity markets. In addition, the IMF predicts that emerging markets will grow twice as fast as those of industrialized countries through this decade. Adding to the attractiveness of emerging markets are the potential diversification benefits. Emerging markets tend to have low correlations with developed markets, thereby providing overall risk reduction benefits to the portfolio. Although there may be a number of factors to explain the exceptional development of emerging markets, the most plausible explanation is that economic reform in these markets has led to a rapid increase in equity flows from the industrial to developing markets.[1]

The deregulation and privatization programs in European emerging markets and capital mobility may increase the volatility of these markets. Policy makers are

[1] Stulz (1997) highlights this; Bekaert and Harvey (1995) and Henry (2000a) empirically show that the financial capital flows from industrial to developing countries benefit both sides.

legitimately concerned because volatility of portfolio flows can have a destabilizing economic impact. The fear of policy makers stems from the fact that flow of foreign funds is typically volatile, with positive inflows in a strong economy and negative outflows in a weak economy. In the long run; however, gradual development and diversification of the markets can lead to lower volatility. Even though the recent bearish markets have affected the developed and developing economies alike, emerging markets have remained on a distinctly positive economic growth path. Economic reforms and the expansion of the European Union, along with the changing political climate worldwide, may create more investment opportunities as well as pose additional challenges and uncertainty in the years to come.

We believe that our contributions from this study are twofold. First, we focus on a large sample of Europe starting from 1988 to 2002. Unlike previous studies,[2] which are limited by either an individual country or a small set of countries, our sample includes the seven countries in Europe with emerging markets. Second, we examine the issues of stability, predictability, and volatility of European emerging stock markets, as these are important issues to portfolio managers and policy makers. Specifically, we examine coefficient stability for Box-Jenkins ARMA representations of weekly returns. In addition, we test the predictability of these equity returns. Finally, we examine volatility effects of expected returns in a GARCH framework. GARCH methodology has been used in the context of developed markets.[3] In this paper, we examine GARCH-based volatility in the context of emerging markets. In contrast to other studies, our use of a battery of statistical tests on a relatively large number of countries aims to examine these emerging markets more robustly and to improve our understanding about them.

We find significant evidence that the emerging markets are stable and that some form of predictability exists. All of the markets we tested show evidence of volatility clustering; however, shocks are not explosive. In addition, we find that two of the seven markets show significant time varying risk premiums.

Literature Review

Studies by various authors such as Divecha, Drach, and Stefek (1992), Haque, Hassan, and Varela (2001), Harvey (1994a, 1995a), Wilcox (1992), and Stone (1990) have documented a low correlation between emerging market returns with those of developed countries. Expected returns are high, as these markets are highly volatile. The individual markets are more volatile; however, diversification across countries reduces international portfolio risk.

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[2] Poshakwale et al. (2001) study two emerging stock markets of Eastern Europe; Harris et al. (2001) focus on one European emerging market; while Kalvinder (1997) studies only two Eastern European emerging markets.

[3] Bekaert and Harvey (1997) and DeSantis and Gerard (1997) all have used GARCH models in developed markets.

Rouwenhorst (1999) finds the factors that drive cross-sectional differences in expected stock returns in emerging equity markets are qualitatively similar to those that have been found in developed equity markets. Simon (2001) finds that for risk-averse investors the use of downside risk measures can result in significant improvements in performance, with particular reference to the estimated allocations in the emerging markets.

Many authors, including Bekaert and Hodrick (1992), Campbell and Hamao (1992), Fama and French (1992), and Harvey, Solnik, and Zhou (1994), have documented the existence of predictable variation in returns of developed countries. The literature also reports evidence against the random walk hypothesis for stock returns (Summers, 1986; Fama and French, 1988; Lo and MacKinlay, 1988; and Poterba and Summers, 1988). Predictable variations in emerging market returns have been documented in Bekaert (1995), Harvey (1995, 1995a, b), Haque et al. (2001, 2004a, b), and Claessens, Dasgupta, and Glen (1995). Buckberg (1995) also finds evidence of predictability in emerging markets, but rejects the hypothesis that lagged price information cannot predict future prices.[4] Bailey et al. (1990) present evidence that stock prices of several Asian markets do not follow random walks. Bessembinder and Chan (1995) examine whether market participants in emerging markets take advantage of profit opportunities that may be present due to deviations from the random walk model.

Haque, Hassan, and Varela (2001) investigate the stability, volatility, risk premiums, and persistence of volatility in the standardized 1988-1998 exchange converted U.S. dollar equity returns of Argentina, Brazil, Chile, Columbia, Mexico, Peru, and Venezuela. All markets except Argentina, Colombia, and Mexico have time-varying risk premiums, which is indicative of risk aversion. In addition, all markets have ARCH/GARCH effects, except Venezuela, which also offers the best potential diversification gains because of low correlation. Haque, Hassan, and Zaher's (2004a) study on ten Asian stock markets uses a nonparametric runs test for weak form of market efficiency and decisively rejects the hypothesis for weak form efficiency. Haque et al. (2004b) examine ten Middle Eastern and African equity markets and find them to be generally stable but unpredictable. The volatilities of these markets are not explosive.

Considerable research has focused on stock market liberalization and volatility (Bekaert and Harvey, 2003a, 2003b; Bekaert, Harvey, and Lumsdaine, 2002a; Kassimatis, 2002; De Santis and Imrohoroglu, 1997; Huang and Yang, 1999; Kim and Singal, 2000; and Aggarwal et al., 1999); however, the empirical evidence is mixed.

[4] Poterba and Summers (1988) indicate that stock index returns may show positive autocorrelation if some of the securities in the index trade infrequently and argue that small stocks trade less frequently than large stocks. Therefore, new information is incorporated into the prices of larger stocks first, then into the prices of smaller stocks. This results in a lag which induces a positive serial correlation.

Studies by different authors also have documented the presence of higher volatility in emerging markets than in developed markets. Harvey and Ferson (1993, 1994b) document that emerging markets have higher volatility than industrial or developed markets. Divecha, Drach, and Stefek (1992), Harvey (1994a, 1995a), Stone (1990), and Wilcox (1992) also provide evidence of high volatility in the individual emerging markets. Low correlation between the developed and the emerging markets reduces the volatilities in portfolios that include securities from developed and emerging markets.

Returns and risk premiums are directly related to the asset's variance and covariance with the market portfolio (Sharpe, 1964; and Black and Scholes, 1974). Glosten, Jagannathan, and Runkle (1993) claim that there is no agreement about the relation between risk and return in pooled cross-section or time-series data. Investors may not demand a high-risk premium if the risky time periods coincide with periods when investors are better able to bear risk (are less risk averse). A riskier future may motivate investors to save more in the present and lower the need for larger premiums, especially in the absence of a risk-free asset. These arguments imply that both a positive and a negative relationship between current return and current variance (risk) are possible. Tesar and Werner (1995) conclude that, despite recent increases in investment in foreign equities, U.S. portfolios remain biased toward domestic equities.[5] There is no evidence of a relation between the volume of U.S. transactions in foreign equities and local turnover rates and volatility of stock returns. Hence, U.S. investments abroad do not appear to be a source of excess volatility or higher turnover on local equity markets.[6]

Volatility clustering has a long history as a salient empirical regularity that characterizes high speculative prices. It was not until recently that applied researchers in finance have recognized the importance of explicitly modeling time-varying second order moments. The ability of ARCH models to provide quality estimates of equity return volatility is well documented. Many studies show that the parameters of a variety of different ARCH models are highly significant; (Bollerslev, 1987; Nelson, 1991; and Glosten et al., 1993), though there is less evidence that ARCH models provide good forecasts of equity return volatility. By using ARCH and GARCH, Akgiray (1989**)** presents various forecasts of market volatility and compares their accuracy. The predictive capabilities of the ARCH and GARCH models constitute further evidence of their overall usefulness as practical models of stock returns.

[5] Gooptu (1993) points out a sharp increase in equity flows in the developing countries in recent times.

[6] Several studies have shown that increased portfolio equity flows to emerging markets led to a decline in the cost of capital in these countries (Bekaert and Harvey, 1997, 2000; Stulz, 1997; Henry, 2000a). Stulz (1997) shows that the stock return data did not support the hypothesis of increased stock return volatility and excessive co-movement among emerging market stock returns.

The Engle (1982) ARCH model, Bollerslev (1986) GARCH (q, p) model, and Engle et al. (1987) GARCH (q, p) - M provide extensions to the GARCH model where the conditional mean is an explicit function of the conditional variance known as the GARCH-M model. Chou (1988) explains that the GARCH-M model provides a more flexible framework to capture various dynamic structures of conditional variance, and allows simultaneous estimation of parameters of interest. The Bollerslev et al. (1992) study states that the GARCH-M model provides a natural tool for investigating the linear relationship between the return and variance of the market portfolio provided by Merton's (1973, 1980) intertemporal CAPM.[7] Poterba and Summers (1986) argue that a significant impact of volatility on stock prices can occur only if a shock to volatility persists over an extended time period.

Using daily indices for modeling volatility on stock prices in Hungary and Poland, Poshakwale and Murinde (2001) find the presence of nonlinearity and conditional heteroskedasticity in these stock indices. Harris and Kucukozmen (2001) examine the return characteristics of the Turkish stock market using two flexible families of distributions. They find daily equity returns to be highly non-normal. Kalvinder's (1997) study on the stock return volatility of two emerging European markets finds no asymmetry in either emerging market; however, asymmetry is found in a stock return series of developed markets.

Data

The data used in this study are from the International Finance Corporation's (IFC) weekly stock market index data for seven European markets. The observation period ranges from December 1988 through August 2002. The observation periods for all countries are not the same due to the fact that many qualified for *emerging market* status at different points in time. The weekly observations differ from most other studies that use either yearly or monthly data. Table 1 shows the market capitalization (US$ millions) and number of stocks in each index as of August 2, 2002. These indices, based on value-weighted portfolios, are designed to serve as benchmarks that are consistent across international boundaries and include stocks that satisfy criteria related to size, liquidity, and industry. The indices, calculated by IFC since 1981, do not consider restrictions on foreign ownership and are calculated in local currencies as well as the U.S. dollar. The conversion to the U.S. dollar for most markets uses exchange rates taken from the *Wall Street Journal* and *Financial Times*. For a multiple exchange rate system, IFC uses the nearest equivalent free market rate or the rate that would apply to repatriation of capital and income. Also,

[7] Using monthly returns, Choudhry (1996) studies volatility and risk premiums before and after the crash of 1987 with respect to six emerging markets by GARCH (q, p)-M. He finds the presence of an ARCH effect for the six markets under study and the persistence of volatility before and after the 1987 crash.

to ensure consistency, IFC only adds or deletes stocks when coverage drops below 50 percent or rises above 70 percent of the total market capitalization.

Table 1—Market Weights in IFC's EMEA Indices as of August 02, 2002

Region	Firms	Market Cap (US $ Mil)	Weights in IFC EMEA	Weights in IFC Comp
Europe				
Czech Republic	14	2335.69	0.95	0.258%
Greece	71	30945.91	12.61	3.421%
Hungary	18	6670.82	2.72	0.738%
Poland	31	7300.75	2.97	0.807%
Russia	18	51335.89	20.92	5.676%
Slovakia	10	144.91	0.06	0.016%
Turkey	58	13923.47	5.67	1.539%
Total - Europe	220	112657.44	45.90%	12.4557%
Latin America	256	123383.4		13.6416%
Asia	1029	535646.2		59.2225%
EMEA	582	245435.00		27.1359%
IFC Composite	1867	904464.6		100.00%

Note: Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East and Africa Index.
Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through August 02, 2002

Weekly nominal excess returns (inclusive of dividends) based on the U.S. dollar are used for the indices rather than local currency as this provides a uniform medium in which to compare performance. The comparison is standardized because inflation differences between countries are captured somewhat with the exchange converted U.S. dollar returns, given that these incorporate inflation through purchasing power parity and the international Fisher effect. The dollar-denominated returns are from IFC's EMDB and are calculated as log of price relatives based on the U.S. dollar for the seven emerging markets. The weekly nominal excess returns are calculated from the percent logarithmic difference between closing prices.

Methodology

The following Box-Jenkins (1976) ARMA (p, q) model is used to test for stability for each emerging market and the composite global and Latin America indices,

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots\ldots \alpha_p y_{t-p} + \varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + \ldots \beta_q\varepsilon_{t-q} \tag{1}$$

where y_t is the return for each market/index (t = 1 to T), α_i is the coefficient on the lagged returns (i = 1 to p), ε_t is the autoregressive error term, and β_j is the coefficient on the lagged error terms (j = 1 to q).

Once the appropriate model in equation (1) is identified and estimated, then it is checked for structural stability. The sample of T observations is split into two, with m observations in the first and n (equal to T- m) in the second. Then equation (1) is identified and estimated for each sub-sample, with the coefficients for the first given by α_{i1} and β_{j1} and the second by α_{i2} and β_{j2}. The F-test is used to test the null hypotheses of no structural change or that the corresponding coefficients for each sub-sample are equal (α_{i1} equals α_{i2} and β_{j1} equals β_{j2}). If the F-test cannot reject the null and α_i is a positive fraction, then returns for the market/index are deemed stable over time. Returns for the seven European stock markets have different time periods. The largest sample has 709 weekly observations, and the smallest has just 344 observations. Therefore, we split the sample into two equal observations for conducting F tests.

To test for adequacy and predictability of returns we use the Ljung-Box Q statistic. The individual t-statistics are obtained from the autocorrelation functions (ACF). We repeat the predictability test with the Lo-MacKinlay (1988) test using a q week holding period. The variance ratio test is used to test for a random walk in returns, i.e., that returns are i.i.d. with a constant mean and finite variance that is a linear function of the holding period, such that deviations from a random walk exhibit some form of predictability in returns. Deviations indicate rejection of the random walk hypothesis and provide evidence that returns are predictable. The variance ratio is

$$\overline{VR}(q)^{a} = 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\hat{\rho}(k). \tag{1a}$$

In the presence of general heteroskedasticity the test statistic,

$$Z(q) = \frac{\sqrt{nq}\left(\overline{VR}(q) - 1\right)^{a}}{\sqrt{\hat{\theta}}} \approx N(0,1), \tag{1b}$$

where the standard error term is

$$\hat{\theta}(q) \equiv 4\sum_{j=1}^{q-1}\left(1 - \frac{k}{q}\right)^{2}\hat{\delta}_{k}\text{ , and} \tag{1c}$$

$$\hat{\delta}(j) = \frac{\sum_{k=j+1}^{nq}\left(p_k - p_{k-1}\ \hat{\mu}\right)^2\left(p_{k-j} - p_{k-j-1} - \hat{\mu}\right)^2}{\left(\sum_{k=1}^{nq}\left(p_k - p_{k-1} - \hat{\mu}\right)^2\right)^2}. \tag{1d}$$

Under the null hypothesis the value of the variance ratio is one. We conclude that returns are predictable when the variance ratio is greater than one.

We also test for weak-form market efficiency using a Runs test to see if the data order is random. This is a nonparametric test because no assumption is made about population distribution parameters. We use this test to determine if the order of responses above or below a specified value (mean) is random. A run is a set of consecutive observations either all less than or all greater than some value.

Volatility, risk premiums, and persistence of volatility are examined using the GARCH (q, p)-M methodology (Engle, 1982; Bollerslev, 1986; Engle and Bollerslev, 1986; and Engle et al., 1987). In this approach, the conditional variance at time t, h_t ($= E_{t-1}\varepsilon_t^2$), is equal to

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2} + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2}$$

where the ARCH model for ε_t is

$$\varepsilon_t = v_t (\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2})^{1/2} .$$

The return generating process is specified by

$$y_t = \mu_t + \delta\, h_t^{1/2} + \varepsilon_t \tag{3}$$

where $\varepsilon_t \sim N(0, h_t)$, v_t = white noise process such that $\sigma^2_v = 1$, v_t and ε_{t-1} are independent.

The size and significance of α_i in equation (2) indicates the magnitude of the effect imposed by the lagged error term ε_{t-i} on the conditional variance h_t. The size and significance of β_i in equation (2) implies the existence of GARCH process in the error terms (volatility clustering). If the size of the sum of α_i and β_i in equation (2) equals one, then current shocks persist indefinitely in conditioning the future variance. The sum of α_i and β_i also represents the change in the response function of shocks to volatility per period such that a value more (less) than unity implies that the response function of volatility increases (decreases) with time. The presence of $h_t^{1/2}$ in equation (3) provides a way to directly study the explicit trade between risk and expected return. The significant influence of volatility on stock returns is captured by the coefficient δ of $h_t^{1/2}$ as it represents the index of relative risk aversion (time varying risk premium).

Empirical Results

The summary statistics for the exchange-converted U.S. dollar weekly returns of seven European emerging markets are shown in Table 2, including mean, standard deviation, Sharpe ratio, skewness, kurtosis, maximum, and minimum. We find that five of seven European markets have positive weekly mean returns. The Czech Republic and Slovakia have negative weekly mean returns; however, this is only significant (at 1 percent) for the Czech Republic. In terms of relative risk-return trade, the highest Sharpe ratio is for Russia, followed by Poland. The skewness and kurtosis measures indicate that the rate of return is not likely drawn from a normal distribution. In general, a kurtosis value of three (3) is associated with a normal distribution. As reported in the table, the excess kurtosis signifies that the distribution has fat tails, and we find that all the European markets display evidence of fat tails. For comparison, we also provide the statistics for two developed markets–the U.K. and the U.S., both of which display excess kurtosis.

Table 2—Summary Statistics. Europe and Two (2) Developed Markets Weekly Returns: 1988-2002 (U.S. $)

Europe Index	obs	Mean	p-value	St dev	SR	SK	p-value	EKU	p-value	Max	Min
Czech Republic	448	-0.001615	0.00168	0.03560	-0.00455	0.11547	0.32002	1.27847	0.00000	0.12670	-0.12628
Greece	709	0.001464	0.40011	0.04630	0.03153	0.27617	0.00274	2.23530	0.00000	0.21285	-0.19786
Hungary	500	0.000930	0.65146	0.04601	0.02021	-0.60984	0.00000	5.99131	0.00000	0.16401	-0.32458
Poland	500	0.002755	0.34004	0.06451	0.04271	-0.15531	0.15750	2.97249	0.00000	0.25014	-0.27934
Russia	344	0.004155	0.37843	0.08738	0.04755	-0.44857	0.00072	3.01350	0.00000	0.35691	-0.39700
Slovakia	344	-0.002671	0.17323	0.03630	-0.07357	-0.08125	0.54017	1.39973	0.00000	0.14565	-0.11841
Turkey	709	0.001136	0.72529	0.08606	0.01320	-0.89570	0.00000	9.14469	0.00000	0.38772	-0.73306
Developed Market Index											
UK	709	0.001150	0.16184	0.02186	0.05260	-0.24023	0.00916	2.82643	0.00000	0.10069	-0.12692
US	709	0.001601	0.04954	0.02168	0.07386	-0.57982	0.00000	3.24118	0.00000	0.07498	-0.12410

Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through August 02, 2002 for Greece, Turkey. In the case of other countries, the start date coincides with the inception of the country's status as an emerging market. SR refers to the Sharpe ratio, SK to skewness, EKU to excess kurtosis. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East, and Africa Index

Table 3A—Correlation Coefficients among Europe and Two (2) Developed Markets Weekly Returns: 1988-2002

Region	Index	Czech Republic	Greece	Hungary	Poland	Russia	Slovakia	Turkey	U.K.	U.S.
Europe	Czech Republic	1.0000	0.3599	0.4884	0.4985	0.3462	0.1728	0.2860	0.1792	0.1489
	Greece		1.0000	0.3810	0.3316	0.2151	0.1394	0.2442	0.2594	0.2847
	Hungary			1.0000	0.5594	0.4316	0.1417	0.3785	0.4119	0.3555
	Poland				1.0000	0.4011	0.0899	0.3019	0.3527	0.3506
	Russia					1.0000	0.1247	0.3209	0.3637	0.2946
	Slovakia						1.0000	0.0736	0.0736	-0.0203
	Turkey							1.0000	0.2461	0.2071
Developed Market	U.K.								1.0000	0.6887
	U.S.									1.0000

Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through August 2, 2002. The start date coincides with the inception of the country's status as an emerging market. Correlations are restricted to the time period for which the data are available. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East, and Africa Index

Table 3B—Asset Allocation for a Minimum Variance Portfolio between European Emerging Markets, UK & US or UK/US. Weekly Returns 1988-2002 (U.S. $)

		Index Weights								
Mean	Variance / St Dev	Czech Republic	Greece	Hungary	Poland	Russia	Slovakia	Turkey	U.K.	U.S.
0.00024	0.00029 / 0.01708	0.12957	0.00000	0.00000	0.00000	0.00000	0.19231	0.00000	0.27061	0.40750
-0.00004	0.00034 / 0.01839	0.15506	0.01598	0.00000	0.00000	0.00000	0.19967	0.00000	0.62929	
0.00019	0.00031 / 0.01763	0.14956	0.00000	0.00000	0.00000	0.00000	0.21819	0.00000	0.63225	

The correlations among the returns are provided in Table 3A. The highest correlation is between the Czech Republic and Hungary (0.4884) followed by Hungary and Russia (0.4316) and then Poland and Russia (0.4011). The lowest correlations are between Slovakia and Turkey (0.0736), Slovakia and Poland (0.0899) and Slovakia and Russia (0.1247). Slovakia has very low correlations with all of the emerging the markets of the region, thereby providing the opportunity for diversification benefits. The correlation between the seven markets, the U.K., and the U.S. are also shown in the table. The highest correlation is between the U.K. and Hungary (0.4119), and the lowest is between Slovakia and the U.S. (-0.0203).

Table 3B shows the asset allocation between the emerging markets, the U.K., and the U.S. We find the greatest diversification benefits by allocating investments across the Czech Republic, Slovakia, the U.K., and the U.S. in accordance with the weights shown in the table. The minimum variance portfolio reduces the risk (standard deviation) and increases the return (mean) when compared to any individual markets. From an investor's point of view, it is also beneficial to have diversification between European emerging markets and the U.S. Interestingly; however, there are no diversification benefits by combining the U.K., rather than the U.S., with these emerging markets. Finally, diversifying within Europe (emerging and developed) may not be a good strategy.

The stability test results reported in Table 4 show that the returns are not stable for Greece at the 5 percent significance level or for Slovakia and Turkey at the 10 percent level. Emerging markets by their nature change rapidly through time. The

Table 4—Stability Test Summary Statistics European Emerging Markets Weekly Returns, 1988-2002 (Based on the U.S. $)

Region–Europe					Stability Test	
Index	Obs	ARMA(Lag)	Coefficient	p-value	F-stat	p-value
Czech Republic	448	AR (1)	0.1891584	0.0000615	0.7285200	0.3938211
Greece	709	AR (1)	0.8685251	0.0000000	3.12125**	0.0447129
		MA (1)	-0.8263536	0.0000000		
Hungary	500	AR (2)	0.1804787	0.0000551	0.2102600	0.6467674
Poland	500	AR (2)	0.1415148	0.0015410	0.5890500	0.4431503
Russia	344	AR (2)	-0.5184996	0.0017368	0.4218900	0.6561518
		MA (2)	0.6948866	0.0000009		
Slovakia	344	AR (2)	0.8408132	0.0000000	2.49433***	0.0840701
		MA (2)	-0.7910642	0.0000048		
Turkey	709	AR (2)	0.1053529	0.0050570	3.49152***	0.0620985

Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through August 02, 2002 for Greece, Turkey. In the case of other countries the start date coincides with the inception of the country's status as an emerging market. Results are based on a Box-Jenkins ARMA (p,q) model, with the structural stability tested using two evenly split sub-samples of the appropriate model with the F-test used to test for the null hypothesis of no structural change, or that the corresponding coefficients for each sub-sample are equal. *, **, and *** denotes significance at 1 percent, 5 percent, and 10 percent, respectively. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East, and Africa Index dismantling of barriers to the flow of capital, both within the country and from external sources, can cause changes in the institutional features and regulatory environment. This is consistent with previous research suggesting that recent changes and institutional features in emerging markets can be an underlying factor in these findings.[8]

Table 5—Autocorrelations and Ljung-Box Q-Statistics

	D-W	Autocorrelations Order				Ljung-Box Statistics		
Index	Statistics	First	Second	Third	Fourth	# of Lags	Q value	p-value
Czech Republic	1.97389	-0.01068	0.04550	0.03254	-0.01701	15	20.62750	0.11157
448 obs						30	33.63230	0.25297
						45	42.99150	0.51478
Greece	1.96211	0.01803	-0.01642	-0.01381	-0.03562	15	12.5557	0.48269
709 obs						30	33.2798	0.22560
						45	49.2754	0.23655
Hungary	2.00490	-0.00332	-0.00794	0.02955	0.04072	15	14.6199	0.40462
500 obs						30	27.2408	0.55871
						45	45.1180	0.42498
Poland	1.92044	0.03848	0.00254	-0.01906	-0.02909	15	18.3047	0.19325
500 obs						30	34.3403	0.22702
						45	59.4885 ***	0.05953
Russia	1.763796	0.1156278	0.0230815	-0.0048942	0.0995952	15	23.6312 **	0.03470
344 obs						30	41.7734 **	0.04554
						45	56.4506 ***	0.08193
Slovakia	1.917091	0.0368513	-0.0182896	-0.0105884	-0.0131421	15	11.8747	0.53794
344 obs						30	27.5358	0.48924
						45	37.6475	0.70204
Turkey	2.062729	-0.0323034	-0.0012917	0.0170729	0.0160063	15	1103633	0.65729
709 obs						30	34.8833	0.20840
						45	58.0377 ***	0.07621

Note: The Ljung-Box statistics jointly test for the presence of autocorrelation up to a specified lag distributed Chi-square (df = # of lag). *, **, and *** denote significance coefficients at the 1 percent, 5 percent and 10 percent level. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East, and Africa Index

The predictability test results based on autocorrelation and Ljung-Box statistics are in Table 5. Russia displays signs of predictability for all the lags shown, while Poland and Turkey show signs of predictability for higher lags (45) at the 10 percent significance level. High autocorrelation in emerging markets indicates the presence of various imperfections in the functioning of these markets. In light of efficient market models, this would imply inefficiency in the markets. We find most of the markets in the group to be unpredictable.

Table 6 reports predictability results based on Lo and MacKinlay (1988), using Z-statistics adjusted for heteroskedasticity for two, four, eight, and sixteen week

[8] See Roll (1989).

holding periods.[9] We find that the Czech Republic and Slovakia show signs of predictability for two, four, and eight week holding periods. Turkey shows signs of predictability for a two week holding period only. The predictability, as found by the Lo and MacKinlay test, may be due to the short time series of our data for some markets. The conventional tests of efficiency were developed for testing markets that are characterized by high levels of liquidity, sophisticated investors with access to high quality and reliable information, and few institutional impediments. The emerging markets are typically characterized by low liquidity, thin trading, and possibly less well-informed investors with access to unreliable information and considerable volatility. Furthermore, efficiency implicitly assumes that investors are rational, where rationality implies risk aversion, unbiased forecasts, and instantaneous responses to information. Such rationality leads to prices responding linearly to new information. Emerging markets, especially during the early years of trading,

Table 6—Variance Ratio Tests of Europe Weekly Returns, 1988-2002 (U.S. $)

Europe		Holding Period of (q) Weeks			
Index		2	4	8	16
Czech Republic	VR(q)	1.309302 *	1.5681378 *	1.7642567 **	1.307610
448 observations	Z(q)	6.546835	4.246348	2.473250	1.578678
	p-value	0.000000	0.000022	0.013387	0.114405
Greece	VR(q)	1.000153	0.964057	1.066297	1.263521
709 observations	Z(q)	0.004080	-0.337951	0.269899	0.684771
	p-value	0.996745	0.735401	0.787245	0.493489
Hungary	VR(q)	0.937616	1.119252	1.247961	1.091453
500 observations	Z(q)	-1.395242	0.942965	0.845714	0.199608
	p-value	0.162956	0.345732	0.397720	0.841793
Poland	VR(q)	1.008433	1.194905	1.316858	1.279105
500 observations	Z(q)	0.188576	1.540866	1.080480	0.609060
	p-value	0.850406	0.123341	0.279920	0.542458
Russia	VR(q)	1.036930	1.240793	1.375531	1.796019
344 observations	Z(q)	0.684945	1.578990	1.062163	1.440817
	p-value	0.493375	0.114359	0.288163	0.149641
Slovakia	VR(q)	1.20309 *	1.43092 *	1.61462 ***	1.86015
344 observations	Z(q)	3.76738	2.82622	1.73872	1.55717
	p-value	0.00017	0.00471	0.08209	0.11947
Turkey	VR(q)	0.917165 **	1.001940	1.065557	1.109770
709 observations	Z(q)	-2.205681	0.018242	0.266204	0.285244
	p-value	0.027412	0.985447	0.793322	0.775460

The variance ratio test based on Lo and MacKinlay (1988) is consistent under heteroskedasticity. Under the random walk hypothesis the value of the variance ratio VR(q) = 1. Q denotes holding period. The test statistic Z(q) is distributed asymptotically normal. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East and Africa Index.

[9] Urrutia (1995), points out that computations of larger variance ratios are not appropriate and would yield spurious results considering the changing nature of the emerging markets.

may be characterized by investors who do not have these attributes.[10] Overall our findings point toward the majority of the markets in the group as being unpredictable. The presence of autocorrelation in the markets may be due to both the economy and capital markets that have been growing at a rapid pace. Autocorrelations are indicators of economic growth rather than evidence against the efficient market hypothesis.[11]

Table 7 reports the nonparametric runs test for testing the weak form of market efficiency. We report the findings at the 1 percent, 5 percent, and 10 percent level. Our findings indicate that weak form efficiency can be rejected for five of the seven European regional markets at the 10 percent level. Although each of the three tests gives a slightly different conclusion on predictability, our results tend to agree in general with Lo and MacKinlay (1988), Poterba and Summers (1988), and Urrutia (1995) in that emerging market in this group are not predictable.

Table 7—Nonparametric Test (Runs Test) of Europe, Weekly Returns (U.S. $) 1988-2002

Region - Europe Index	Mean	Observed # of Runs	Expected # of Runs	Observations above Mean	Observations below Mean	p-value
Czech Republic*	-0.0016	196	224.884	229	219	0.0000
Greece***	0.0015	330	354.636	337	372	0.0634
Hungary **	0.0009	228	250.324	237	263	0.0451
Poland	0.0028	238	250.424	238	262	0.2649
Russia*	0.0042	146	172.977	174	170	0.0036
Slovakia	-0.0027	164	172.296	183	161	0.3683
Turkey **	0.0011	329	355.443	350	359	0.0468

Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through August 2, 2002 for Greece and Turkey. In the case of other countries, the start date coincides with the inception of the country's status as an emerging market. *, **, and **** denotes significance at 1 percent, 5 percent and 10 percent level, respectively. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East and Africa Index

The volatility, risk premiums and persistence of shocks to volatility for all markets are reported in Table 8. For the sake of brevity, we do not report volatility modeling for each of the seven European emerging markets. The empirical investigation conducted by our GARCH-M model also reports excess kurtosis, skewness, and Q statistics for the residuals. We find evidence of significant volatility clustering in each of the seven European emerging stock markets.[12] Our ARCH parameter (α,

[10] Campbell, Lo, and MacKinlay (1997) report that after four decades of research on the random walk hypothesis, it is now widely accepted that the efficient market hypothesis should be viewed as a relative rather than an absolute concept.

[11] Lucas (1978) states that the existence of autocorrelation in the financial markets does not necessarily imply market inefficiency.

[12] Haque et al. (2001, 2004a,b) present evidence of volatility clustering in Latin American, Asian, Middle Eastern, and African emerging markets with shocks decaying over time.

Table 8—GARCH (1, 1) Europe, Weekly Returns (U.S. $), 1988-2002

Models: 1) $y_t = \mu_t + \delta_t * h_t^{1/2} + \varepsilon_t$ y_t = stock index return

2) $\varepsilon_t / \psi_{t-1} \sim N\ (0, h_t)$ μ_t = mean, y_t conditional on past information (y_{t-1})

3) $h_t = \alpha_0 + \Sigma^q_{i=1} \alpha_i * (\varepsilon_{t-i})^2 + \Sigma^p_{i=1} \beta_t * h_{t-i}$ $\alpha_0 > 0, \alpha_i \geq 0, \beta_i \geq 0$

Region - Europe Index	μ	δ	α_0	α	β	Σ(α+β)*	LF	Ku	Sk	Q (30)
Czech R.	-0.001615	-0.017046	0.000339	0.325724	0.411247	0.736970	1295.96	0.98999	-0.08497	27.0702.
448 observations	0.337491	0.70998	0.00079	0.00034	0.00085	0.00503		0.0000	0.4638	0.35238
Greece	0.001464	- 0.021962 *	0.000706	0.314322	0.405723	0.720040	1830.7381	2.37975	0.2512	37.9674.
709observations	0.400112	0.00914	0.00000	0.00000	0.00000	0.00000		0.00000	0.00639	0.03494
Hungary	0.000930	0.063465	0.000305	0.224713	0.655251	0.879960	1305.5542	6.07666	-0.62685	49.8559.
500 observations	0.651456	0.15161	0.00413	0.00043	0.00000	0.02818		0.00000	0.00000	0.00222
Poland	0.002755	0.033672	0.000329	0.219743	0.703906	0.923650	1175.8205	2.99527	-0.15117	40.3241.
500 observations	0.340038	0.44603	0.01109	0.00038	0.00000	0.055663		0.00000	0.16845]	0.02700
Russia	0.004155	0.106746 **	0.000439	0.128666	0.808203	0.936870	702.72004	2.70369	-0.36477	45.9387.
345 observations	0.378433	0.046447	0.008793	0.000243	0.000000	0.042522		0.00000	0.00588	0.0045
Slovakia	-0.002671	-0.081545	0.000613	0.174566	0.373913	0.548480	958.17269	1.43703	-0.07792	27.0106.
344 observations	0.173228	0.12755	0.04004	0.02191	0.10042	0.04861		0.00000	0.55632	0.30395
Turkey	0.001136	-0.001351	0.000704	0.097240	0.813038	0.910280	1403.9916	8.97042	-0.90269	35.7827.
709 observations	0.725292	0.97106	0.00038	0.00033	0.00000	0.00270		0.00000	0.00000	0.07496

Note: Significance levels in italics. A Chi-square ($\chi 2$) test is used to test $(\alpha + \beta)^*$ equal to one. LF is the log likelihood function value and Ku the kurtosis of the residuals. Sk is the skewness of the residuals and Q(30) is the Ljung - Box statistics serial correlation of the lags in the residuals. Ku, Sk, and Q(30) statistics are calculated from models and are different from those reported in Tables 2 and 5. The*, **, and *** denotes a significance coefficient at the 1 percent, 5 percent and 10 percent level. Europe (E) is part of EMEA index. EMEA refers to the Europe, Middle East and Africa Index model 3 in Table 8) is less than unity for all seven markets, signifying that shocks are not explosive. Economic interpretations of the ARCH effect in stock returns have been provided within both micro and macro frameworks. According to Bollerslev et al. (1992) and other studies, the ARCH effect in stock returns could be due to clustering of trade volumes, nominal interest rates, dividend yields, money supply, oil price index, etc.

The significant influence of volatility on stock returns is captured by the coefficient $h_t^{1/2} * \delta$ (model 1 in Table 8). The coefficient δ represents an index of relative risk aversion. We find the influence of volatility on stock returns (δ) to be positive; however, the time-varying risk premia for two markets (Hungary and Poland) are insignificant. The Czech Republic, Slovakia, and Turkey, on the other hand, have negative (δ), but insignificant time varying risk premium. We find that Greece is the only market in this group to have a negative, but significant, time-varying risk premium at the 1 percent level, while Russia has a positive and significant time varying risk premium at the 5 percent level. A significant and positive δ implies that investors trading stocks are compensated with higher returns for bearing higher risk, while a significant negative δ indicates that investors are penalized for risk bearing. As reported in Table 4, Greece, Turkey, and Slovakia show signs of a structural break, which can lead to higher volatility; however, only Greece has a negative and significant time-varying risk premium. Although Russia shows no sign of structural break, we find the market to have a positive and significant time-varying risk premium. We find that five of the seven markets do not show any evidence of a significant time-varying risk premia. We also find that all seven markets displaying ARCH effects have excess kurtosis for the residuals, indicating that in all cases the residuals have thicker tails than a normal distribution.

The persistence of shocks to volatility is measured by ($\alpha + \beta$) in the GARCH-M model. According to Engle and Bollerslev (1986), if $\alpha + \beta = 1$ in the GARCH (1,1)-M model, a current shock persists indefinitely in conditioning the future variance. Because the sum $\alpha + \beta$ represents the change in the response function of shocks to volatility persistence, a value greater than unity implies that the response function of volatility increases with time and a value less than unity implies that shocks decay with time (Chou, 1988). The closer to unity the value of persistence measure, the slower is the decay rate. For the seven markets, we fail to reject $\alpha + \beta = 1$, i.e., shocks to volatility are permanent. This implies that the conditional variance is nonstationary. Poterba and Summers (1986) state that a significant impact of volatility on stock prices can only occur if a shock to volatility persists over a long time. Engle and Ng (1993) see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock. They believe changes in market volatility merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume and practices or patterns which in turn are driven by a number of factors such as macroeconomic policy shifts in investor tolerance for risk and increased uncertainty.

Table 9 reports the performance of post sample predictions for two years of weekly data for all of the markets. The mean squared errors (MSE) from one step ahead forecasts from ARMA models specified in Table 4 are compared to the MSEs from naïve models that assume a random walk. The random walk model performs surprisingly well given its simplicity. As shown by the ratio of MSEs in Table 9, a random walk model outperforms the ARMA models (i.e., relative MSE > 1) in two countries. In the worst case, the random walk model underperforms by 2 percent in Slovakia (0.9813), compared to the ARMA model. On the other hand, the random walk model outperforms ARMA models by .00008 percent in the Russian market. This evidence indicates that finding significant predictable components does not necessary lead to marked improvement in forecasting ability and that these components may be just artifacts of a particular sample rather than features of the true data-generating process.

Table 9—Comparison of Mean Squared Errors of One Step Ahead Forecast from ARMA Models to a Naïve Random Walk Model

Europe Index	Obs	MSE ARMA Models	Std Error	MSE Naïve Model-RW	Std Error	Relative MSE MSE(ARMA) < SE(RW)
Czech Republic	104	0.0010275	0.0012103	0.0010268	0.0012456	1.0006
Greece	104	0.0019687	0.0037156	0.0019937	0.0036757	0.9875
Hungary	104	0.0018183	0.0032253	0.0018312	0.0032278	0.9929
Poland	104	0.0019483	0.0033029	0.0019757	0.0032944	0.9861
Russia	104	0.0036207	0.0059599	0.0035922	0.0061196	1.0079
Slovakia	104	0.0013012	0.0021759	0.0013260	0.0021637	0.9813
Turkey	104	0.0155445	0.0565382	0.0155706	0.0566694	0.9983

Post sample predictions performance period 20000802-20020802 (104 weekly observations). The naïve models assume a random walk to forecast one step ahead. Relative MSE of models is the ratio of MSR (ARMA) to MSE (Naïve)

Conclusion

In this paper, we provide an extensive empirical investigation on the correlation, stability, predictability, volatility, time-varying risk premium, and persistence of shocks to volatility in the seven European emerging stock markets. The majority of these markets recently gained emerging status. We find four of seven emerging markets have returns that are stable over time. On the issue of predictability in the emerging markets, we find varying results on predictability using three different tests; overall, the markets seem to be unpredictable. Our findings on volatility indicate that all seven markets show evidence of volatility clustering; however, the shocks are not explosive. Regarding persistence of shocks to volatility, none of the markets has permanent shocks. In general, European emerging markets are stable (except Greece, Slovakia, and Turkey), unpredictable, and have volatility clustering with only two of seven markets having significant time-varying risk premium and offering diversification benefits.

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