The influence of foreign portfolio investment on informational efficiency: Empirical evidence from Central and Eastern European stock markets

Alexandru Todea*, Anita Pleşoianu

Department of Finance, Faculty of Economics and Business Administration, Babes-Bolyai University, 58-60, Teodor Mihali St, 400591 Cluj-Napoca, Romania

Abstract

This paper presents empirical evidence suggesting that foreign portfolio investment had a positive and significant influence on the informational efficiency of eleven Central and Eastern European stock markets during the period 1999–2010, regardless of the type of dependence — short or long run — taken into account when determining the measure of the degree of informational efficiency. Furthermore, considering the asymmetric effects of the portfolio flows, we have generally found a direct and strong relation between the net positive flows and the degree of informational efficiency. Our panel results also show that market capitalization represents a significant explanatory factor for the presence of short run dependence, while liquidity is associated with the presence of long run dependence. After isolating the common shocks in time, market volatility seems to have an even greater impact on efficiency.

© 2013 Elsevier B.V. All rights reserved.

1. Introduction

Based on the argument that a financial market cannot be informationally perfectly efficient, Campbell et al. (1997) introduced the concept of relative efficiency, that is the efficiency of one market measured against another. The main feature of most studies regarding absolute efficiency is represented by the fact that conclusions are drawn from the entire studied sample, without taking into account the possible alternation of efficiency with inefficiency subperiods. Identifying subperiods of efficiency/inefficiency and ranking the relative market efficiency are most often accomplished by using the time-varying or rolling window approach. Thus, Cajueiro and Tabak (2004, 2005) estimate Hurst exponents in each window to test for long run dependence and use the median as a statistical measure when ranking the markets. Lim and Brooks (2009, 2010) used the rolling bicoherence test statistic that focuses on nonlinear dependence, arguing that a more appropriate indicator for relative efficiency would be the percentage of time windows in which the market exhibits significant nonlinear dependence. Zunino et al. (2008) proposed a stock market inefficiency ranking by considering the multifractality degree as a measure of inefficiency.

We can identify several interdependent channels through which the presence of foreign investors in Central and Eastern European (CEE) stock markets should lead to an increase in their degree of informational efficiency. First, foreign portfolio investment raises the liquidity in these markets, which stimulates the arbitrage activity (Chordia et al., 2008), and thus, there should be a faster capitalization of information into stock prices and smaller departures from a random walk benchmark. Second, according to Bae et al. (2006), foreign investors require transparency and stricter disclosure rules and these, in their turn, improve the information environment in emerging stock markets. Third, according to the theoretical model of Albuquerque et al. (2009), local investors underreact to global news because they do not have immediate access to them or do not have enough analysis capacity. In contrast, foreign investors obtain information faster and have superior capacity to incorporate global news in security prices (Bae et al., 2012). Finally, foreign investors’ need to manage risks will lead to the development of derivative markets with stabilizing effect on spot markets. Lien and Zhang (2008) reviewed the literature on the price discovery function of derivative markets and show that a financial derivative market stimulates the capital inflows into emerging markets. At the same time, the use of financial derivatives leads to higher volatility and accelerated outflows.

The empirical results of the few studies in the literature are contradictory. For instance, Tabak (2003), using an error-correction model, shows that foreign portfolio inflows are mainly responsible for the increased efficiency in the Brazilian stock market. Li et al. (2004) showed on a sample of 17 emerging stock markets that higher firm-specific variation is significantly correlated with greater capital market openness, especially in the economies with sound institutions. On the other hand, Lagoarde-Segot (2009) identifies in the case of 29 emerging markets a negative impact of international portfolio equity flows on market efficiency. Such a result can be best accounted for by the foreign investors’ preference for technical rather than fundamental analysis. A similar result is obtained by Lim and...
Kim (2011) in a study of 23 emerging markets. A possible explanation is that on emerging markets positive autocorrelations of returns are generated by foreign investors engaged in positive feedback trading strategies, according to the theoretical model developed by De Long et al. (1990). Bariviera (2011) fails to identify a significant relation between the presence of foreign investors and efficiency in the case of the Thai stock market. Recently, Bae et al. (2012) have shown on a sample of 4840 stocks in 21 countries that greater investibility reduces price delay to global market information leading to an increase of the degree of efficiency.

The objective of this paper is to empirically investigate the relation between stock market efficiency and foreign portfolio investment in CEE. From the beginning, we must underline that a sensitive issue is how the informational efficiency of a stock market is measured. According to Lim and Kim (2011), in most studies, the deviation from random walk is perceived as a deviation from efficiency, deviation due to the presence of short and/or long run dependence. Unlike the vast majority of studies that focus on one type of dependence only, this paper brings a first important contribution by investigating both types of dependences through the Generalized Spectral (GS) test and the Generalized Hurst Exponent (GHE) test. Our second contribution consists in studying the relation between stock market efficiency and foreign portfolio investment by using different panel regressions in which we include a set of control variables that captures the features of the investigated markets and in which we allow for the effects of asymmetric portfolio flows. Finally, given the contradictory results in literature, this paper highlights the relation between efficiency and foreign portfolio investment in the case of CEE stock markets.

The paper is organized as follows: Section 2 describes the two tests used to measure the efficiency. Section 3 presents the data and the methodology. Section 4 reports the empirical results. The final section summarizes the conclusions.

2. Measuring the degree of stock market efficiency

This section addresses two issues related to weak-form stock market efficiency. First, we present arguments according to which the presence of short and long run dependence in stock returns indicates market inefficiency. Second, we describe the tests chosen to detect these correlations.

2.1. Short and long run dependence and stock market inefficiency

In informationally efficient markets stock prices are in permanent equilibrium; they fluctuate only in response to the arrival of new information to the market. A quick incorporation of information in stock prices would determine a random movement given by the random nature of this information, which implies the impossibility to predict the stock price and to obtain systematic profits due to the absence of short and long run dependence in return series. On the contrary, a mis-reaction to information will lead to the emergence of linear and nonlinear dependence in returns and, implicitly, to a potential predictability.

A series of behavioral models proposed by Barberis et al. (1998) or Hong and Stein (1999) explains how phenomena like over- and under-reaction can generate linear dependence in returns. De Long et al. (1990) developed a theoretical model which demonstrates that investors’ over-reaction could lead to positive autocorrelations of returns. In the case of stock indices, Froot and Perold (1995) showed that positive autocorrelations of returns can be generated by the slow dissemination of market-wide information.

In the literature there are various theoretical developments which justify the presence of nonlinear dependence in stock return series. First, Cootner (1962) explains the nonlinear dynamics through the interaction between noise traders and arbitrage traders in the presence of transaction costs. A series of arbitrage models developed later by Dumas (1992) or Sercu et al. (1995) strengthens Cootner’s arguments. Second, the slow market response to unexpected shocks, caused by the financial crises (Lazar et al., 2012; Lim et al., 2008a) or by several economic and political events (Lim et al., 2008b), leads to stock price deviations from equilibrium, thus generating nonserial dependence. Third, the recent ‘behavioral finance’ literature has developed a series of nonlinear behavioral models of the interactions between heterogenous agents even in the absence of transaction costs. Thus, McMillan (2005) considers that the cognitive movements and the limited ability of investors to perform arbitrage operations lead to deviations from the fundamental value, generating nonlinear dynamics. Fourth, in the case of emerging stock markets, Schatzberg and Reiber (1992) believe that certain characteristics and imperfections, such as high transaction costs and low liquidity, delay the incorporation of new information into prices, generating nonlinearities in returns.

Another strand of the literature has brought attention to the predictability due to long run correlations in return series, easily exploitable for substantial profits. This feature is generated especially by the heterogeneity of market participants. There are many ways to describe this heterogeneity, but the most promising approach is the one that considers time dimensions. It is known that stock markets include various investors with very different investment horizons ranging from several seconds (noise traders, market makers) to several years (pension funds). Thus, the information set that is most relevant differs according to the investment horizon. Short-term investors focus primarily on market sentiment and technical information; long-term investors base their decisions on movements in fundamentals (Kristoufek, 2012). Contrary to the common assumption, there is no privileged investment horizon in the market. The interaction of investors with different time scales generates various effects, such as volatility cluster and trend persistence.1

2.2. Brief description of the tests

2.2.1. Generalized spectral test

This test proposed by Escanciano and Velasco (2006) is recently used to investigate the efficiency of stock markets (Kim et al., 2011; Lim and Luo, 2012), of currency markets (Escanciano and Lobato, 2009a) and carbon emission allowance market (Charles et al., 2011).

Let \( Y_t \) be the stationary time series of returns. Escanciano and Velasco (2006) propose to test the null hypothesis \( H_0 : E[Y_t | Y_{t-1}, Y_{t-2}, \ldots] = \mu \), where \( \mu \) is a real number, using a pairwise approach. That is, \( H_0 : m_j(y) = 0, j \geq 1 \) almost surely, where \( m_j(y) = E[Y_t - \mu | Y_{t-j} = y] \) and \( \mu \) is the mean, against the alternative hypothesis \( H_1 : P(m_j(Y_{t-j}) \neq 0) > 0 \) for some \( j \geq 1 \). A nonlinear measure of dependence is considered \( \gamma_j(x) = E[Y_t - \mu | e_{t+j}] \) where \( x \) is a real number, this exponential weighting function been used to measure the conditional mean dependence in a nonlinear time series framework. The above null hypothesis is consistent with the following \( \gamma_j(x) = 0 \) \( \forall j \geq 1 \), almost everywhere.

The authors use the generalized spectral distribution function:

\[
H(\lambda, x) = \gamma_0(x)\lambda + 2\sum_{j=1}^{\infty} \gamma_j(x) \sin(jnin\lambda) / jn \left( \lambda^{2} / n \right)
\]

with the sample estimate as follows: \( H(\lambda, x) = \gamma_0(x)\lambda + 2\sum_{j=1}^{n-1} (1-j/n)^{2} \gamma_j(x) \sin(jnin\lambda) / jn \), where \( (1-j/n)^{2} \) is a finite sample correction factor. \( \gamma_j(x) = (n-j)^{-1} \sum_{t=n-j+1}^{n} (Y_t - \overline{Y}_{n-j}) e^{2j\pi x t} \) and \( \overline{Y}_{n-j} = \]

1 Dacorogna et al. (2001) refer to these features as ‘characteristically relativistic effects’ – the dynamic interaction between different market components relative to each other, rather than relative to the news that has impacted the market.
(n−j)−1∑j=n+1∞Yj. Under the null hypothesis the generalized spectral distribution function becomes H(λ,x) = y0(λ)x, and the test is based on the difference between H(λ,x) and H0(λ,x) ∼ y0(λ)x, as follows:

\[ S_π(λ,x) = \frac{(n/2)^{1/2}}{\lambda} \int \left[ H(λ,x) - H_0(λ,x) \right] \]

\[ = \sum_{j=1}^{n-1} \left( n-j \right)^{1/2} \sqrt{2} \sin(\pi j/\pi n). \]

To evaluate the distance of S_π(λ,x) to zero, for all possible values of λ and x, the Cramer-von Mises misfit is used:

\[ D^2_n = \int \frac{1}{2\pi} \sum_{j=1}^{n-1} \left( \frac{1}{n-j} \int [h(\lambda,x) - \lambda^x \gamma(x)] \right)^2 \]

\[ = \sum_{j=1}^{n-1} \left( n-j \right)^{1/2} \sqrt{2} \sin(\pi j/\pi n). \]

The test statistic follows asymptotically a weighted sum of independent chi-squared distributions. As the asymptotic distribution of the test depends on the data generating process in a complicated way, Escanciano and Velasco (2006) propose implementing the test using a wild bootstrap procedure. In this paper, in order to obtain the two-tailed p-value of the test, we set the number of bootstrap iterations to 1000.

It is important to note that the GS test is consistent against all pairwise alternatives and it is capable to detect a wide range of linear and non-linear dependence in the conditional mean, allowing for a general form of unknown conditional heteroscedasticity. Through Monte Carlo simulations, Charles et al. (2011b) compare the power properties of this test with other competitors and highlights its superiority especially against nonlinear dependence. Moreover, its good asymptotic properties recommend it in a rolling window approach.

2.2.2. Generalized Hurst exponent

GHE was first proposed by Barabasi and Vicsek (1991) and recently re-explored for the financial time series by Di Matteo et al. (2005) and Cajueiro et al. (2009). The parameter H, called the Hurst exponent, displays the long memory property of the time series and it can take values in the range 0 < H < 1. H = 0.5 suggests two possible processes — either an independent or a short-term dependent process. If H > 0.5, auto-covariances decay hyperbolically and are positive so that the process is persistent. In this case a positive return is statistically more likely to be followed by another positive return and vice versa. On the other hand, if H < 0.5, the auto-covariances are negative and the process is anti-persistent. This process implies that a positive return is more statistically probable to be followed by a negative return and vice versa.

Let X(t) denotes the logarithmic price of a stock market index on a time t. Detection of long run dependence and estimation of GHE are based on q-th order moments of the increments of the process X(t):

\[ K_q(\tau) = E[X(t+\tau) - X(t)]^q, \]

which scales as K_q(\tau) ∝ (\tau)^{q\beta}, where the time-interval \( \tau \) can vary between 1 day and \( \tau_{\text{max}} \) days. According to Di Matteo et al. (2005) we set \( \tau_{\text{max}} = 19 \) and \( q = 1 \) to evaluate \( K_1(\tau) \). H(1) describes the scaling behavior of the absolute values of the increments and its value is expected to be close to the classical Hurst exponent.

It is a known fact that the stock returns of the emergent stock markets are not normally distributed and are heavy-tailed. Barunik and Kristoufek (2010) studied how the sampling properties of the Hurst exponent estimate change with fat tails. They ran Monte Carlo simulations to find out how rescaled range analysis, multifractal detrended fluctuation analysis, detrending moving average and the generalized Hurst exponent approach estimate the Hurst exponent on independent series with different heavy tails. The results showed that GHE is robust to heavy tails in the underlying process and provides the lowest variance.

3. Data and methodology

3.1. Data

As in previous studies, we have chosen to conduct the market efficiency tests using daily closing values of market value-weighted equity indices, namely for the twelve CEE stock markets: BET Index (Romania), BUX Index (Hungary), CROBEX Index (Croatia), ISE-100 Index (Turkey), OMXR Index (Latvia), OMXT Index (Estonia), OMXV Index (Lithuania), PX 50 Index (the Czech Republic), RTS Index (Russia), SAX Index (the Slovak Republic), SOFIX (Bulgaria) and WIG Index (Poland).

In panel regressions we use a proxy measure for the informational efficiency as a dependent variable and the foreign portfolio investment (includes net inflows from equity securities other than those recorded as direct investment) as an independent variable. The choice of the independent de facto variable is based on the argument that it measures the intensity of the activity of foreign investors in emerging markets, while various de jure stock market openness measures quantify the access on these markets. In addition, Quinn et al. (2011) note that de jure measures do not reflect the extent to which actual capital flows evolve in response to legal restrictions and may not capture subtle, but possibly important differences between countries’ capital control regimes.

At the same time we include three control variables whose influence on efficiency has been empirically tested in the literature, namely liquidity, market capitalization and volatility. The proxy variable for liquidity is considered the turnover ratio, which is the total value of shares traded divided by the average market capitalization. A high liquidity stimulates the arbitrage activity and leads to an increase of the degree of efficiency. Chordia et al. (2008) or Chung and Hrazdil (2010) formulated and tested a series of hypotheses which sustain this relation. The second control variable is the market capitalization of a listed company (as a share of Gross Domestic Product), A direct relation between this variable and the degree of efficiency is supported by various rankings of markets which were built based on indicators that take into account short run dependence (Lim, 2007; Todea and Gherman, 2012) or long run dependence (Kristoufek and Vosvrda, 2013). The third control variable, volatility, is measured as the standard deviation of the daily returns of stock markets in the interval t. A direct relation between efficiency and volatility is supported not only by the model prediction of Sentana and Wadhwani’s (1992), but also by empirical and theoretical arguments from literature, in favor of an indirect relation.\(^2\) The annual data for the foreign portfolio investment, turnover ratio and the market capitalization are taken from the World Bank’s World Development Indicators database.

The time series cover the sample period from January 1999 to December 2010, except for the three Baltic countries and Bulgaria, for which the time series begin in January 2000. All the values of these indices collected from Thomson Datastream are denominated in their respective local currency units. The data is transformed into a series of continuously compounded percentage returns, \( Y_t = 100 \cdot \ln(P_t/P_{t-\gamma}) \), where \( P_t \) and \( P_{t-\gamma} \) denote two consecutive trading days.

\(^2\) See Lim and Kim (2011, p. 2233) for more discussions.
3.2. Panel methodology

To investigate the empirical relation between foreign portfolio investment and the degree of informational efficiency, we estimate the following unbalanced panel regression:

\[ IE_{it} = a_0 + a_1 NEI_{it} + MV_{it} + a_3 X_{it} + \delta_i + \theta_t + \epsilon_{it} \]

(1)

where \( IE_{it} \) is an inverse measure of informational efficiency for market \( i \) in the interval \( t \). \( NEI_{it} \) represents the net equity inflows, followed by the set of control variables, namely, market return volatility \( (MV_{it}) \) and a vector of variables that measures the degree of market development \( (X_{it}) \), namely turnover ratio and market capitalization. Note that \( \delta_i \) represents the country effects that are intended to control for time-invariant country-specific factors, \( \theta_t \) are the fixed effects that control for common shocks (global financial crisis for example), and \( \epsilon_{it} \) is the error term. Country specific unobserved effect \( (\delta_i) \) should be considered to compensate for the omission of other factors that affect informational efficiency such as macro-level institutions (Eleswarapu and Venkataraman, 2006), transaction cost (Lagoarde-Segot, 2009), culture (Chui et al., 2010) or short-sale constraints (Saffi and Sigurdsson, 2011). Common shocks in time have an impact on market efficiency, therefore parameter estimation will be done with and without time fixed effects.

Random effects are tested by the Breusch–Pagan Lagrange multiplier test, while fixed effects are examined by the F test. If using both tests, the null hypothesis is not rejected, and the pooled OLS regression is favored. If the null hypothesis of both tests is rejected, we use a robust test suggested by Wooldridge (2002, p.290) to choose between fixed and random effects. The random effect estimators are consistent if the null hypothesis of this test is accepted. We always report results robust to serial correlation and heteroskedasticity in cross-section using cluster correction, which is consistent with the recommendations of Petersen (2009).

Positive (negative) \( NEI_{it} \) implies funds flowing into (out of) a country, on balance. Because there is a possibility that the sign of \( NEI \) has a different effect on efficiency we also estimate models that allow for asymmetric portfolio flow effects, i.e., separate coefficients for positive and negative portfolio inflows:

\[ IE_{it} = a_0 + a_1^+ NEI_{it} + a_1^- NEI_{it} + a_3^+ MV_{it} + a_3^- X_{it} + \delta_i + \theta_t + \epsilon_{it} \]

(2)

where \( NEI_{it} = NEI_{it}I_{\text{NEI}>0}, \text{and} \ NEI_{it} = NEI_{it}I_{\text{NEI}<0} \) and \( l \) is an indicator function of the condition. Since \( IE_{it} \) is an inverse measure of efficiency, a negative value of the parameter \( a_l \) indicates a positive impact of inflows on efficiency. If \( a_2 \leq 0 \), the greater the outflows the higher the degree of market inefficiency because the censored variable \( NEI_{it} \) takes negative or 0 values.

Both GS and GHE tests yield good results only on large enough samples, of at least 300 observations for the GS test \(^4\) and 500 for the GHE test.\(^5\) For this reason the interval \( t \) is considered equal to 2 years (approximately 500 sessions), but the quantification of efficiency is different.

In the case of the GS test we will choose the rolling window approach in each interval \( t \) because we observed a high temporal variability of the acceptance probability of the null hypothesis (\( p \)) and an increased sensitivity of the GS test to the choice of the first day of the sample.\(^6\) The application of a rolling window eliminates the aforementioned biases and provides a more accurate overview on the market efficiency degree. Therefore, \( p \) is computed for a window of 300 observations, and then the sample is rolled one point forward eliminating the first observation and including the next one for a re-estimation of the \( p \). For each index, we determine in \( t \) the percentage of time windows for which \( p \) is less than 0.05, as a statistical indicator of efficiency.\(^7\) Because this percentage is bounded within the interval [0,1], we apply a logistic transformation to the variable, so that \( IE_{it} \) takes values between \(-\infty \) and \(+\infty\). In contrast, the estimation for the GHE test will be carried out on the whole interval \( t \) for each index because in a rolling window approach the window length must be of at least 500 observations to offer a robust statistical power and also because the Hurst exponents exhibit a higher temporal stability. Since deviation from 0.5 indicates the presence of long run dependence, the indicator measuring the efficiency will be \( IE_{it} = [\text{GHE} - 0.5] \). \( NEI_{it} \) is determined as an average value in each interval \( t \). \( MV_{it} \) is measured by the sample standard deviation of daily stock returns computed for each index in each interval \( t \). \( X_{it} \) is an empirical proxy for stock market development and is computed for the interval \( t \) as the logarithm of one plus the turnover ratio (namely market capitalization).

4. Empirical results

4.1. Main results

The results from the application of the GS test in the rolling window approach, in each interval \( t \), are summarized in Fig. 1. The higher values of percentage indicate more persistent stock price deviations from random walk, and hence lower degree of market efficiency. We observed a time varying degree of market efficiency and also the fact that the most important markets in the region appear to be more efficient. To some extent, not only the increase of efficiency in the period of crises 2007–2008, but also its deterioration in the last interval 2009–2010 are surprising. Fig. 2 displays the estimated GHE in each interval \( t \), revealing once more that in the case of more developed markets in the region the deviation from random walk is smaller, while for markets like those of Croatia, Estonia, Lithuania and the Slovak Republic there is no clear trend toward efficiency in Hurst exponents.

Table 1 reports the coefficient estimates for regressions Eq. (1) with and without the time period dummies, using the variables that measure the market development both separately and together. The highly significant association with a negative sign between \( NEI \) and \( IE \), regardless of how the efficiency is measured, indicates a direct relation between foreign portfolio investment and informational efficiency. This fact proves the positive impact of foreign investors on the informational efficiency of CEE stock markets.

Analyzing further, we observe that as the stock markets have a greater importance in economy, namely a higher ratio of market capitalization to GDP, the intensity of short run dependence is getting lower. On the other hand, liquidity, measured by the turnover ratio, is proved to be an explanatory factor for the presence of long run dependence. The direct association between efficiency and liquidity on CEE stock markets is consistent with both the theoretical literature (Campbell et al., 1993) and the empirical results of other studies

\(^3\) This test is conducted in STATA using the xtoverid command proposed by Schaffer and Stillman (2010).

\(^4\) Charles et al. (2011a, 2011b) showed, through Monte Carlo simulations performed on samples of 100, 300 and 500 observations, that the GS test shows excellent power against a wide range of linear and nonlinear models, with no size distortion. However, the test is more powerful when the sample is larger. Therefore, in this study the GS test will be applied in rolling windows of 300 observations since a rolling window of 500 observations would be too long considering the sample period covered.

\(^5\) The Monte Carlo study of Barunik and Kristoufek (2010) which highlights the superiority of GHE test against other competitors was performed on simulated time series of different lengths form \( 2^0 \) to \( 2^6 \). Thus, the conclusions drawn by the authors are valid only if the sample is of at least \( 2^6 \) observations.

\(^6\) Todea and Zoićăş-Ienciu (2008) showed that by considering the first day of the sample effect the results are different from those obtained in the previous studies, additional subperiods rejecting the random walk hypothesis being revealed.

\(^7\) We followed Lim (2007) who noted that the percentage of time windows for which \( p \) is less than 0.05 provides a more useful framework for assessing the market efficiency than the median which is subject to criticism.
As regards the sign of the link between volatility and efficiency there is no consensus in the literature. Our results, according to which the higher the volatility, the higher the degree of market efficiency, are consistent with Sentana and Wadhwani’s (1992) model prediction, but inconsistent with the arguments and empirical results of Lim and Kim (2011). Note that the relation between volatility and market efficiency becomes more powerful when in the model we isolate the common effects in time on the efficiency such as the significant increase in volatility in all markets during the interval 2007–2008 as a result of the global crisis for example.

Table 2 presents the asymmetric regression estimates for flows, keeping in each model that proxy for market development that has been a significant influence factor on efficiency in previous investigations. The negative regression coefficient on $\text{NEI}_{it}$ indicates a direct relation between efficiency and net positive flows (inflows), which again proves the positive effect on efficiency of foreign portfolio investment in the CEE stock markets. The inflows lead to an increase of market liquidity, fact that stimulates the arbitrage activity and, thus, increases the degree of market efficiency. The impact of $\text{NEI}_{it}$ (outflows) on efficiency is generally not significant. The fact that only 21 of the 68 values of $\text{NEI}_{it}$ are different from 0 may explain to some extent this result. Studies on much larger samples could shed light on this area.

4.2. Robustness checks

Next we check the robustness of results in several ways, as depicted in Table 3. As a first test of robustness we changed the intervals $t$ of two years for which the variables are quantified, starting with the interval 2000–2001. Thus, we obtained balanced panels of 60 observations for the period 2000–2009. The negative and significant parameters corresponding to net equity inflows indicate again a direct relation with the degree of efficiency, regardless of investigating short run (in model (1)) or long run dependence (in model (2)).

A second category of robustness tests involves the use of others de facto variables for foreign portfolio investment (PF), namely the cross-border portfolio investment holdings in equity securities obtained from Coordinated Portfolio Investment Survey Guide, in models (3)–(4), and the portfolio equity measure assembled by Lane and Milesi-Ferretti (2007) in models (5)–(6). The significant parameters of these variables reconfirm the direct relation between the degree of efficiency and foreign portfolio investment, except the case of model (6).

A third category of robustness tests, models (7)–(8), consists in using the de jure stock market openness measure, proposed by Schindler (2009). It was built for the entire period 1999–2010 based on the information contained in the Annual Report on Exchange Arrangements and Exchange Restrictions (AREAR) published annually by the International Monetary Fund. The index employed ($\text{KA}_{\text{Equity}}$) is determined as an average of four binary dummy variables for the following components: purchase locally by nonresidents, sale or issue abroad by residents, purchase abroad by residents and sale or issue locally by nonresidents. For each component, a restricted market was coded with 1 and an unrestricted market with 0. The study of the relation between efficiency and de jure stock market openness measure is of interest, especially for the policymakers. Regardless of how the IE variable is measured, the relation is not significant, a situation which is not surprising if we analyze the $\text{KA}_{\text{Equity}}$ indicator on countries. For example, Poland, which is the market with the highest degree of efficiency, is also the most restrictive, while Bulgaria and the Baltic countries have a lower degree of efficiency and the fewest restrictions on capital. Also, for some countries such as the Czech Republic or Hungary an increased number of restrictions can be observed after 2005.

Finally, a fourth category of robustness tests involves replacing the GS test with the automatic portmanteau test proposed by Escanciano and Lobato (2009b) and the GHE test with the Multifractal Detrended Fluctuation Analysis (MF-DFA) introduced by Kantelhardt et al. (2002). The automatic portmanteau test is an improved version of the portmanteau test, robust to heteroscedasticity, introduced by Lobato et al. (2001). Choosing the optimal number of lags is achieved by a fully data-dependent procedure, ensuring a compromise between Akaike’s information criterion and the Bayesian information criterion. The test statistic asymptotically follows the chi-squared distribution with one degree of freedom. According to Charles et al. (2011b) this is a high-performance test especially against linear dependence. The MF-DFA is a generalization of detrended fluctuation analysis (DFA) proposed by Peng et al. (1994) and has the advantage that it can be used for nonstationary time series. It is based on the examination of deviations from polynomial fit of different moments $q$. For $q = 2$ we obtain the classical Hurst exponent. The estimates of model (9) show that net equity inflows remain significant factors affecting the degree of efficiency even when IE is measured with the automatic portmanteau test. The insignificant relation in model (10), when the MF-DFA is employed, can have at least two explanations. First, according to Barunik and Kristoufek (2010), compared with the GHE, the Hurst exponent estimated through MF-DFA can be biased when stock returns are not normally distributed and are heavy-tailed. Second, it is possible that the measure we proposed, $\text{IE}_{\text{eq}} = [\text{GHE} - 0.5]$, may not be the most appropriate to assess the degree of efficiency. Further research has to take into account more complex measures, proposed by Zunino et al. (2009) or Kristoufek and Vosvrda (2013).
Table 1
Net equity inflows and stock market efficiency.

<table>
<thead>
<tr>
<th>IE-GS test</th>
<th>Net equity inflows</th>
<th>Market volatility</th>
<th>Turnover ratio</th>
<th>Market capitalization</th>
<th>Constant</th>
<th>Prob. &gt; F</th>
<th>Prob. &gt; ( \chi^2 )</th>
<th>Xtoverid</th>
<th>Cross-section effects</th>
<th>Time fixed effects</th>
<th>Max (VIF)</th>
<th>( R^2 )</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>–2.16–10**</td>
<td>–43.75**</td>
<td>–0.064</td>
<td>–</td>
<td>1.51***</td>
<td>0.000</td>
<td>0.616</td>
<td>0.085</td>
<td>Random</td>
<td>No</td>
<td>1.38</td>
<td>0.085</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.22–10***</td>
<td>–63.53**</td>
<td>–0.12</td>
<td>–</td>
<td>2.44***</td>
<td>0.000</td>
<td>0.643</td>
<td>0.163</td>
<td>Random</td>
<td>Yes</td>
<td>2.70</td>
<td>0.163</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–1.98–10**</td>
<td>–42.85**</td>
<td>0.073</td>
<td>–</td>
<td>1.51***</td>
<td>0.000</td>
<td>0.859</td>
<td>0.080</td>
<td>Random</td>
<td>No</td>
<td>1.29</td>
<td>0.080</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.24–10**</td>
<td>–62.91**</td>
<td>–</td>
<td>–</td>
<td>2.46***</td>
<td>0.000</td>
<td>0.843</td>
<td>0.166</td>
<td>Random</td>
<td>Yes</td>
<td>2.86</td>
<td>0.166</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.00–10**</td>
<td>–43.86**</td>
<td>–</td>
<td>–</td>
<td>1.51***</td>
<td>0.000</td>
<td>0.945</td>
<td>0.0791</td>
<td>Random</td>
<td>Yes</td>
<td>1.39</td>
<td>0.0791</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.28–10**</td>
<td>–64.99</td>
<td>–</td>
<td>–</td>
<td>2.50***</td>
<td>0.000</td>
<td>0.912</td>
<td>0.164</td>
<td>Random</td>
<td>Yes</td>
<td>2.88</td>
<td>0.164</td>
<td>68</td>
</tr>
</tbody>
</table>

Table 2
Net equity inflows and stock market efficiency – asymmetric portfolio flows ‘effects’.

<table>
<thead>
<tr>
<th>IE-GS test</th>
<th>Net equity inflows</th>
<th>Market volatility</th>
<th>Turnover ratio</th>
<th>Market capitalization</th>
<th>Constant</th>
<th>Prob. &gt; F</th>
<th>Prob. &gt; ( \chi^2 )</th>
<th>Xtoverid</th>
<th>Cross-section effects</th>
<th>Time fixed effects</th>
<th>Max (VIF)</th>
<th>( R^2 )</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>–2.82–10***</td>
<td>–43.97**</td>
<td>–0.135</td>
<td>–</td>
<td>0.096***</td>
<td>0.000</td>
<td>0.560</td>
<td>0.195</td>
<td>Random</td>
<td>No</td>
<td>1.39</td>
<td>0.195</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.20–10**</td>
<td>–65.23**</td>
<td>–0.128</td>
<td>–</td>
<td>0.135***</td>
<td>0.000</td>
<td>0.438</td>
<td>0.251</td>
<td>Random</td>
<td>Yes</td>
<td>2.70</td>
<td>0.251</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–67.77–11**</td>
<td>–2.05**</td>
<td>–0.097</td>
<td>–</td>
<td>0.096***</td>
<td>0.000</td>
<td>0.443</td>
<td>0.107</td>
<td>Random</td>
<td>No</td>
<td>1.29</td>
<td>0.107</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–3.00–12**</td>
<td>–2.40</td>
<td>–0.167</td>
<td>–</td>
<td>0.135***</td>
<td>0.000</td>
<td>0.645</td>
<td>0.195</td>
<td>Random</td>
<td>Yes</td>
<td>2.86</td>
<td>0.195</td>
<td>68</td>
</tr>
<tr>
<td></td>
<td>–2.20–12**</td>
<td>–2.69</td>
<td>–0.195</td>
<td>–</td>
<td>0.135***</td>
<td>0.000</td>
<td>0.713</td>
<td>0.249</td>
<td>Random</td>
<td>Yes</td>
<td>1.37</td>
<td>0.249</td>
<td>68</td>
</tr>
</tbody>
</table>

Note: The dependent variables are an inverse measure of informational efficiency for country i in the interval t. Robust t-statistics in parentheses; **, *** indicate statistical significance at 10%, 5% and 1% levels. For all estimated models the hypothesis of multicollinearity is investigated using the variance inflation test (VIF). In all cases the VIF values are lower than 3 which indicates low risk of multicollinearity.
of the GHE test, respectively. The code of the GS test

Acknowledgments

investors who diversify their portfolios internationally.

results of such studies are useful in CEE stock markets, maybe such as economic freedom, protection of

de jure stock market openness measures are

There are only a few studies in the literature that have investigat-
ed the relation between stock market efficiency and foreign portfolio


