THE PERSISTENCE OF PRICING INEFFICIENCIES IN THE STOCK MARKETS OF THE EASTERN EUROPEAN EU NATIONS

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Received: 17 March 2013
Accepted: 2 September 2013

ABSTRACT: *This paper applies a range of metrics to test for the presence of weak form market efficiency in the Eastern European countries that joined the EU in 2004, we test both the years prior to and following accession. The results from our tests indicate that, despite the expectations of many previous studies, even after entering the EU the stock markets of these countries still do not conform to even the loosest form of market efficiency. We improve and extend previous studies by incorporating liquidity controls, applying a wider range of methodologies and by using individual stocks rather than indices.*

Keywords: *Emerging Stock Markets; European Union; Eastern European Transition Countries; Stock Market Efficiency; Weak Form Market Efficiency*

JEL Classification: F36, G14

1. INTRODUCTION

The debate over stock market efficiency is one of the central tenets of capital market theory. The issue is particularly pertinent for the Eastern European nations that joined the European Union in 2004[4] (hereafter the EE EU nations) because of the stock market's role in the ongoing privatization process and also as it serves as an important barometer with which to measure the progress made by these countries in the transition from planned to market economies. In this paper we examine weak form market efficiency (WFME) as defined by Fama (1970) which, as the loosest form of market efficiency, requires nothing more than current period returns "fully reflect" earlier period returns and thus successive price movements are independent of each other: failure to conform to WFME means that stronger forms of efficiency are not present and the stock market's pricing can be considered inefficient.

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[4] These are the transition nations that joined the EU on 1st May 2004, namely Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia

A significant body of research into WFME in the EE EU nations exists. Jagric et al (2005) test for WFME in the region, the authors found that the stock market indices of Czech Republic, Hungary, Russia and Slovenia all exhibited weak form inefficiencies in the form of long memory in stock returns. Worthington and Higgs (2004) examined WFME in both developed and emerging stock markets in Europe, of the emerging markets covered (Czech Republic, Hungary, Poland and Russia) only the Hungarian stock market could be considered weak form efficient. Gilmoore and McManus (2001) applied a range of WFME tests to the larger EE EU economies (Czech Republic, Hungary and Poland) over the period 1990 to 2000 and found that significant weak form inefficiencies exist in the stock exchanges of all three countries. Chun (2000) reported that while the Hungarian market may be weak-form efficient, the stock markets of the Czech Republic and Poland were inefficient. Nivet (1997) and Gordon and Rittenberg (1995) also found that the Polish stock market could not be considered weak form efficient. Ahmed, Rosser and Uppal (2010) found strong evidence of nonlinear speculative bubbles in Czech Republic, Hungary and Poland. Mihailov and Linowski (2002) and Dezelan (2000) find evidence of weak-form inefficiency in the Latvian and Slovenian stock markets respectively.

We further the above studies in a number of ways. Firstly, we incorporate liquidity controls into our work. It is quite possible that illiquid shares exhibit properties consistent with weak form inefficiency; WFME tests, especially those in emerging markets, need to incorporate liquidity controls in order to ensure that the results are not distorted by apparently predictable returns from infrequently traded securities. In our view this is an omission in the studies listed above that reduces the robustness of results. Indeed, Benic and Franic (2008) found a substantial level of illiquidity in the stock markets of Central and Eastern Europe. Secondly, we include all eight transition countries that acceded to the EU in 2004, while the studies listed above include between one and five of the countries: by considering the region in its entirety, we are able to ascertain a broader and more complete perspective of WFME in the EE EU nations. Thirdly, Jagric, Podobnik and Kolanovics's (2005) dataset ends in 2004, the datasets in the other papers cited end before this. In contrast, our dataset starts in 1999 and runs to the end of 2008. Fourthly, much of the previous work examining WFME in the EE EU nations has been based on stock market indices rather than individual stocks: previously reported findings that the stock markets are inefficient may be due to only a small proportion of the indices' constituents or simply the manner in which the indices are constructed. By using individual stocks, our work provides an important validation of previous work. Furthermore, using individual stocks provides a broader view than using indices alone and may help to provide insight into the underlying causes of the inefficiency. Finally, we use the same metrics as Worthington and Higgs (2004), this is a much broader range than the other cited papers use: our wider range of tests allows us to cross check and validate our results. Furthermore, the results from our work further the existing literature by providing a pre- and post-EU accession comparison.

While the majority of early studies found that returns on the newly-created stock exchanges of the EE EU nations did not conform to WFME, many expected these inefficiencies to disappear over time. Wheeler et al (2002) studied the Warsaw Stock Exchange during its first five years of operation; the authors expected the exchange to become more efficient over time, citing increasing experience of market participants, more sessions per week, more analysts offering better research, and better investor relations departments. Rockinger and Urga (2001) surmised that their finding that the Hungarian market had a lower level of predictability than the markets of Czech Republic, Poland and Russia was partly due to the fact that the Budapest Stock Exchange had operated for a longer period of time. Again, suggesting that the stock markets of the EE EU nations should become more efficient simply due to the passage of time. Moor and Wang (2007) examined the volatility levels on the stock markets of the Czech Republic, Hungary, Poland, Slovenia and Slovakia and concluded that volatility declined as the nations moved into the EU. Worthington and Higgs (2004) hypothesised that there may be a link between the absence of WFME and the small size of some stock markets in the EE EU; this implies pricing efficiency will improve with the growth of these markets. Jagric et al (2005) also proposed a tentative link between a stock market's size and its pricing efficiency. From a macroeconomic perspective, Claessens et al (2000) suggested that EU integration will drive the development process in the EU transition countries. Rapacki and Prochniak (2009) and Vojinovic, Oplotnik and Prochiniak (2010) examined real beta and sigma convergence in the EE EU nations during the process of EU accession, an important extension of this work is to question whether nations' stock markets are also converging as authors such as Csaba (2011, p11) report that "financial institutions play a pre-eminent role in all phases of transformation". Bekaert et al (2013) report that EU membership reduces equity market segmentation.

We test WFME in the EE EU nations over periods 1.1.1999 to 31.12.2003 and 1.1.2004 to 31.12.2008 to determine whether the increasing experience of market participants over time, EU accession and the increasing number of stocks listed, larger market capitalisations and increased turnover in the region has caused markets to become more efficient. Contrary to the expectations of the majority of studies listed above, our tests are all in broad agreement that the equity markets of the EE EU nations do not conform with WFME and this situation has not been substantially affected by accession to the EU. Therefore, none of the factors that previous researchers expected to become catalyst to drive the markets towards higher efficiency have materialized. Despite the passage of almost a generation since the creation of the EE EU stock markets, a significantly larger number of listed securities and 5 years since EU accession, these markets still cannot be considered to conform to WFME: these results pose the question of what changes are needed to improve efficiency of financial markets in these countries or whether these stock exchanges will ever attain pricing efficiency.

2. DATASET

Our dataset consists of stocks included in the Dow Jones Stoxx EU Enlarged Total Market index, using data obtained from Bloomberg. This is a free-float capitalization-weighted index covering the countries have joined the EU since 2004. We excluded stocks from Bulgaria and Romania as the paper is concerned with the countries that joined the EU in

2004. We excluded stocks from Cyprus and Malta as we are only investigating transition countries. Our dataset covers the period from the 1st January 1999 to 31st December 2008, split into subperiods 1st January 1999 to 31st December 3003 (pre-accession) and 1st January 2004 to 31st December 2008 (post-accession). The reason for the use of subperiods lies in the broader range of methodology employed, such as liquidity controls and the use of individual stocks rather than indices, that does not allow direct comparison of our post accession results with previous studies. Although 1st May was the actual accession date, the effects of accession were earlier – this is the reason why we include the entirety of 2004 in our dataset. We did not extend our dataset past 2008 because of the collapse in financial markets.

We use daily Bloomberg last prices and log returns calculated as:

$$\Delta y_{it} = \log(y_{it}) - \log(y_{it-1})$$

Where:
y_{it} = price of stock i at time t

The descriptive statistics for the two datasets are shown in Table 1.

The increasing number of IPOs caused the number of stocks in our post accession dataset to increase to 151 from 97 in our pre accession dataset. As Poland is by far the region's largest economy, it is logical that the country's stock exchange has the largest weight in our dataset; what is interesting is that the number of stocks quoted on the Warsaw Stock Exchange has almost doubled from 55 to 102 between 1999 and 2004, while few new stocks appeared on the other exchanges. Because our dataset contains only a single stock from each of Latvia and Slovakia we are sceptical that we can make any inferences about the stock markets of these countries.

Average returns over the pre-accession period are positive, the financial crisis that began in 2007 resulted in negative returns over the post-accession period. Despite the volatility ensuing from the stock market downturn that began in 2007, the standard deviation of our dataset for 2004-2008 is lower than for 1999-2003, with only Slovenia recording higher volatility. The skewness of our datasets moves from positive to negative, indicating that while over period 1999-2003 there was a greater probability of a large decrease rather than a large increase in stock prices, the opposite was true for period 2004-2008. However, as the skewness readings for 1999-2003 and 2004-2008 are both close to zero, it is hard to draw any firm conclusions. The kurtosis of our dataset decreased significantly between 1999-2003 and 2004-2008, with only the single Latvian stock recording an increase. The Jacque-Bera statistic is used to test the null hypothesis that stock returns are normally distributed. From the associated p-values, it is clear that only stocks listed on the Budapest Stock Exchange over period 1999-2003 could have returns claonsidered to be normally distributed at any conventional level of significance. The results from the Jacque-Bera test are in broad agreement: returns on the stock markets of the EE EU nations are not normally distributed. However, it is clear the Jacque-Bera test is significant

Table 1: *Descriptive Statistic*

	Number of Stocks		Mean		Standard Deviation		Skewness		Kurtosis		Jarque-Bera		Jarque-Bera P Value	
	1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008
Entire Region	97	151	0,05%	-0,03%	3,31%	2,64%	-0,01	0,01	34,07	13,27	401.433	14.812	0,00	0,00
Czech Republic	5	7	0,05%	0,00%	2,33%	2,25%	-0,35	-0,61	10,23	15,45	3.443	7.750	0,00	0,00
Estonia	5	8	0,08%	-0,16%	5,05%	2,73%	-4,17	-0,51	141,87	10,67	2.620.152	4.281	0,00	0,00
Hungary	8	8	0,00%	0,02%	2,43%	2,41%	0,05	-0,02	9,58	8,93	7.557	2.077	0,04	0,00
Lithuania	10	10	0,17%	0,01%	6,60%	2,42%	1,94	-0,46	89,32	12,81	992.031	5.575	0,00	0,00
Latvia	1	1	0,04%	-0,05%	2,77%	2,24%	0,17	0,36	8,43	15,21	1.500	7.636	0,00	0,00
Poland	55	102	0,03%	-0,02%	3,14%	2,79%	0,03	0,10	20,43	13,21	252.419	16.014	0,00	0,00
Slovakia	1	1	0,08%	0,06%	3,90%	1,81%	-2,38	-0,44	25,08	13,92	14.601	5.511	0,00	0,00
Slovenia	12	14	0,08%	-0,05%	1,60%	2,09%	0,19	0,37	34,74	16,69	161.628	30.662	0,00	0,00

Our dataset is based on stocks in the Dow Jones Stoxx EU Enlarged Total Market index, we only use the transition countries that joined the EU on 1st May 2004.

All calculations are based on daily stock returns calculated on natural logarithms of Bloomberg last prices in local currencies.

Mean is calculated as an arithmetic mean calculated for stocks on an individual basis and then equally weighted for the entire region/individual exchanges

Standard deviation, skewness and kurtosis are calculated on daily returns equally weighted for the entire region/individual exchanges

The skewness and kurtosis inputs for the Jarque-Berra are the same as those reported in this table due to high kurtosis, rather than skewness, therefore the parametric models we apply still return robust results.

3. METHODOLOGY

The tests we employ fall into four categories: tests of serial independence, unit root tests, multiple variance ratio tests and liquidity. We chose to replicate the methodology of Worthington and Higgs (2004) for the serial independence, unit root tests and multiple variance ratio tests because of the broad range of WFME tests applied by the authors and the recognition it received in the literature. Griffin et al (2010) use a range of tests similar to the ones employed in this paper, they question whether it is feasible to make statements about relative market efficiency internationally unless one can control for the information environment. While our dataset covers nations with substantial similarities, we cannot rule out the possibility that our results have been distorted by this. While our dataset covers a large geographic area, the majority of stocks are quoted on the Warsaw Stock Exchange. To control for any Polish bias, we perform the tests for both the region as a whole and the individual countries.

3. 1 Tests of serial independence

A time series is said to be serially correlated if a regression of a time series of returns with its own lags yields statistically significant results:

$$E(\Delta y_{it}|\Delta y_{it-1}) = \beta_1 + \beta_2 \Delta y_{it-1}$$

Where:

$E(\Delta y_{it}|\Delta y_{it-1})$ = the expected value of Δy_{it} given Δy_{it-1}

β_1 = the regression intercept

β_2 = the regression slope

Unlike serial correlation, the runs test is non-parametric and therefore does not require the returns to be normally distributed. Runs tests determine whether a time series follows a random walk by counting the number of consecutive positive or negative observations and comparing it to an expected value *(E(R))*:

$$E(R) = \frac{N + 2N_U N_D}{N}$$

Where:
N = Number of observations

N_U = *Number of positive observations*
N_D = *Number of negative observations*
R = *Number of runs*

We use the expected value and variance values (V(R)) to calculate a test statistic, Z:

$$V(R) = \frac{2N_u N_D(2N_D N_D - N)}{(N)^2(N-1)}$$

$$Z = \frac{R - E(R)}{\sqrt{V(R)}}$$

The null hypothesis is that the returns can be considered to follow a random walk process. Rejection of the null hypothesis indicates that the stock's returns are non-random and contravene WFME. In order to test whether EU accession resulted in an increase in WFME, we use a z-test to determine if the percentage of stocks considered statistically significant at a particular significance level is statistically different between the pre- and post-accession datasets.

3.2 Unit root tests

Unit root tests are used to determine whether the log returns of stocks in our dataset is stationary, i.e. whether it has constant statistical properties; if stocks follow a random walk process, stock returns should be non-stationary. We use three variants, Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and Kwaitkowki, Phillips, Schmidt and Shin (KPSS).

ADF is the most well-known unit root test, the null hypothesis is that the data is nonstationary. The measure is calculated by running the following regression:

$$\Delta y_{it} = \beta_0 + \beta_1 tr + \alpha_0 y i_{t-1} + \alpha_p \sum_{p=1}^{q} \Delta y_{it-p} + \varepsilon_{pt}$$

Where:
α = the coefficients to be estimated
q = number of lagged terms
β_0 = intercept
β_1 = trend coefficient
tr = trend

MacKinnon's critical values are then applied to determine the significance of α.

The PP test, developed by Phillips and Perron (1988), extends ADF to allow errors to be independent and heteroscedastic. For a complete derivation, see Phillips and Perron (1988).

While the ADF and PP tests have null hypothesis of nonstationarity, the KPSS test has a null hypothesis of stationarity. Reversing the null hypothesis provides a useful validation check for the results from the ADF and PP tests. The reader should consult Kwiatkowski et al. (1992) for a full derivation. As with the tests of serial independence, we apply a z-test to determine whether the results from the pre- and post-accession datasets can be considered statistically different.

3.3 Multiple Variance Ratio Tests

The third set of statistics employed are multiple variance ratio (MVR) tests. This approach was developed by Lo and MacKinlay (1988, 1989) and Chow and Denning (1993) who constructed the MVR tests in order to detect both autocorrelation and heteroscedasticity in returns. This is important because if stocks follow a random walk, the variance of returns should rise as a linear function to the number of observations. That is, the variance ratio of the returns over qq period must be equal to $q\sigma^2 q\sigma^2$. The variance ratio (VR) is calculated as:

$$VR(q) = \frac{\sigma^2(q)}{\sigma^2(1)}$$

Where:
$\sigma^2(1)$ = variance of daily log returns
q = number of periods used for the sampling interval
$\sigma^2(q) = (1/q)$ multiplied by the variance of q-daily returns

If stocks conform to the random walk process, VR should not be statistically different to one. In line with the methodology of Worthington and Higgs (2004), the sampling intervals used for q were 2, 5, 10 and 20 days. For a more in depth overview of MVR methodology or a complete derivation, the reader should consult Worthington and Higgs (2004) or Chow and Denning (1993) respectively. We also apply a z-test to determine whether the pre- and post-accession results are statistically different.

3.4 Liquidity Controls

Studies frequently conclude that liquidity is related to future returns. Examples of such work include Amihud and Mendelson (1986, 1989), Chordia et al (2001), Jones (2002), Amihud (2002), and Brennan et al (1998). Datar et al (1998) demonstrate a negative correlation between liquidity, as measured by turnover, and returns. Haugen and Baker (1996) found that liquidity is one of several generic factors that explain returns across global stock markets. Brzeszczynski et al (2011) found that trading intensity affected beta calculations for stocks listed on the Warsaw Stock Exchange and thus had serious ramifications for corporate finance decisions.

The relatively small size of the stock markets of the EE EU countries raises the concern that our results could be distorted by liquidity issues. Liquidity is an elusive concept, consequently in Table 5 we employ three widely used measures to control for it: i) Market capitalization ii) Average volume divided by shares outstanding iii) Bid-ask spread divided by share price. We create liquidity portfolios by assigning a rank (1 (low) to 5 (high)) to every stock for each of the three liquidity measures. Then we separate the combined results from Tables 2, 3, and 4 into five liquidity ranked portfolios in order to examine the effects of liquidity on the tests employed; we repeat this for each of market capitalization (Panel A) average volume divided by shares outstanding (Panel B) and Bid-ask spread (Panel C).

4. RESULTS

The results from the tests of serial independence, unit root tests and multiple variance ratio tests are shown in Tables 2, 3 and 4 respectively. As we cover a large geographic region, each table also provides a geographic breakdown of the results. While around one-third of our dataset is listed outside Poland, the shares are listed on a lot of different exchanges; no exchange other that the Warsaw Stock Exchange has more than 14 shares in the dataset. This makes inferences for individual countries difficult.

4.1 Tests of serial independence

Table 2 shows the results from the tests of serial independence, the serial correlation coefficient and the runs test.

Looking at all the stock exchanges in the dataset, even at the 0.01 level of significance, almost one third of the stocks in our dataset return significant t-statistics from the serial correlation regressions for both the pre- and post-EU accession periods. Whilst there has been a marginal decrease in the number of stocks statistically significant at the 0.01 level between the pre- and post-accession datasets, the z-test reveals that the difference is not statistically significant. 43% of stocks in our dataset can be considered serially correlated at the 0.1 significance level for the pre-accession period; this rises to 66% for the post-accession period. The z-test reveals that the increase in the number of stocks exhibiting serial correlation at the 0.05 and 0.1 levels is statistically significant at 0.01, indicating that prices of stocks listed in the EE EU nations may have actually become less efficient. Looking at the individual stock exchanges, it can be seen that the results from the stock exchanges of other countries are largely consistent with those from the Warsaw Stock Exchange. Across the majority of stock exchanges most stocks exhibit properties consistent with serial correlation, at least at the 0.1 level. The z-test reveals no statistically significant difference between the pre- and post-accession datasets. Thus we can comfortably reject the null hypothesis that returns in the stock markets of the EE EU are not serially correlated.

Table 2: *Tests of Serial Independence*

		Serial Correlation T Statistic			Runs Test		
		1999-2003	2004-2008	Z Test	1999-2003	2004-2008	Z Test
Entire Region							
% of Observations Significant at	1%	31%	28%	0,41	22%	19%	0,47
	5%	39%	54%	- 2,23	38%	38%	- 0,04
	10%	43%	66%	- 3,45	46%	49%	- 0,40
% of Negative Observations		15%	42%		64%	69%	
Czech Republic							
% of Observations Significant at	1%	40%	29%		20%	0%	
	5%	60%	43%		40%	29%	
	10%	60%	71%		60%	43%	
% of Negative Observations		0%	29%		80%	57%	
Estonia							
% of Observations Significant at	1%	60%	50%		40%	38%	
	5%	60%	63%		60%	50%	
	10%	60%	63%		60%	63%	
% of Negative Observations		60%	75%		20%	63%	
Hungary							
% of Observations Significant at	1%	13%	38%		13%	38%	
	5%	38%	50%		13%	63%	
	10%	50%	63%		13%	75%	
% of Negative Observations		38%	50%		13%	38%	
Latvia							
% of Observations Significant at	1%	0%	100%		0%	0%	
	5%	0%	100%		0%	0%	
	10%	0%	100%		0%	0%	
% of Negative Observations		0%	0%		100%	0%	
Lithuania							
% of Observations Significant at	1%	40%	70%		70%	30%	
	5%	70%	90%		90%	50%	
	10%	70%	90%		90%	70%	
% of Negative Observations		30%	20%		90%	90%	
Poland							
% of Observations Significant at	1%	13%	16%		11%	18%	
	5%	16%	48%		27%	35%	
	10%	22%	63%		40%	44%	
% of Negative Observations		11%	48%		71%	74%	
Slovakia							
% of Observations Significant at	1%	100%	0%		100%	100%	
	5%	100%	0%		100%	100%	
	10%	100%	0%		100%	100%	
% of Negative Observations		0%	0%		0%	100%	
Slovenia							
% of Observations Significant at	1%	100%	71%		25%	7%	
	5%	100%	71%		50%	36%	
	10%	100%	71%		50%	50%	
% of Negative Observations		0%	0%		58%	50%	

All calculations are based on stock returns calculated on natural logarithms of Bloomberg last prices in local currencies.
Serial correlation is calculated using one day lags
Runs tests calculations are based on the sign of returns

When the runs test was applied to our dataset, about one fifth of stocks yielded statistically significant results even at the most stringent 0.01 level for both the 1999-2004 and 2004-2008 datasets. Around half of both the pre- and post-accession datasets can be considered significant at the 0.1 level. Stocks listed on the Riga Stock Exchange perform poorly in the runs tests, but the dataset only contains one stock from this country; excluding Latvia, the non-Polish stock markets have similar results to the entire dataset.

4.2 Unit root tests

Table 3 shows the results from the three sets of statistics that form the unit root tests. The null hypothesis of the ADF and PP tests is that the time series has a unit root. The KPSS test reverses the null hypothesis and assumes that the time series has no unit root.

Both the ADF and PP tests reject the null hypothesis, even at 0.01, for all stocks in both the pre- and post-accession datasets. We can comfortably reject the null hypothesis of nonstationarity for all stocks. Needless to say, there is no country variation here. Both tests clearly indicate that the returns of all stocks in the dataset are stationary, that is follow a deterministic rather than stochastic trend; inconsistent with a random walk.

Out of all the metrics we employ, only the KPSS test indicates that stationarity may have declined between the pre- and post-accession periods. The KPSS statistic is insignificant for less than half of all stocks at the 0.01 level of significance for the post-accession dataset, indicating that we cannot reject the null hypothesis of no unit root; yet for our pre-accession dataset, only 5% of stocks have KPSS statistics that can be considered statistically significant at the 0.01 level. Whilst almost three quarters of post-accession stocks have KPSS statistics that can be considered statistically significant at 0.1, the corresponding figure for the pre-accession nations is only around one quarter. The z-test reveals that there is a statistically significant increase in the KPSS statistic between the pre- and post-accession datasets. The results from Poland are almost identical to those for the region as a whole, indicating little regional variation.

While the KPSS statistic is less conclusive than ADF or PP, we can still confidently infer that all three unit root tests employed indicate that returns of many stocks listed in the EE EU nations are stationary, leading us to reject the null hypothesis that stocks follow a random walk.

4.3 Multiple Variance Ratio Tests

Table 4 shows the results from the MVR tests using sampling intervals of two days, 5 five days, 10 days and 20 days; corresponding to one day, one week, one fortnight and one month.

Table 3: *Unit Root Tests*

		ADF		Phillips-Perron Test		KPSS Test		
		1999-2003	2004-2008	1999-2003	2004-2008	1999-2003	2004-2008	Z Test
Entire Region								
% of Observations	1%	100%	100%	100%	100%	5%	46%	- 6,81
Significant at	5%	100%	100%	100%	100%	13%	64%	- 7,86
	10%	100%	100%	100%	100%	25%	72%	- 7,31
	Average	-29,27	-28,88	-33,76	-31,09	0,26	0,79	
	Absolute Average	29,27	28,88	33,76	31,09	0,26	0,79	
Czech Republic								
% of Observations	1%	100%	100%	100%	100%	0%	0%	
Significant at	5%	100%	100%	100%	100%	0%	14%	
	10%	100%	100%	100%	100%	20%	29%	
	Average	-31,61	-28,49	-33,00	-32,15	0,16	0,34	
	Absolute Average	31,61	28,49	33,00	32,15	0,16	0,34	
Estonia								
% of Observations	1%	100%	100%	100%	100%	0%	63%	
Significant at	5%	100%	100%	100%	100%	0%	75%	
	10%	100%	100%	100%	100%	20%	75%	
	Average	-31,57	-28,50	-34,43	-30,91	0,24	0,88	
	Absolute Average	31,57	28,50	34,43	30,91	0,24	0,88	
Hungary								
% of Observations	1%	100%	100%	100%	100%	0%	50%	
Significant at	5%	100%	100%	100%	100%	0%	75%	
	10%	100%	100%	100%	100%	0%	75%	
	Average	-31,32	-31,86	-31,37	-35,00	0,13	0,65	
	Absolute Average	31,32	31,86	31,37	35,00	0,13	0,65	
Latvia								
% of Observations	1%	100%	100%	100%	100%	0%	100%	
Significant at	5%	100%	100%	100%	100%	0%	100%	
	10%	100%	100%	100%	100%	0%	100%	
	Average	-36,60	-35,06	-36,58	-35,10	0,27	1,04	
	Absolute Average	36,60	35,06	36,58	35,10	0,27	1,04	
Lithuania								
% of Observations	1%	100%	100%	100%	100%	30%	90%	
Significant at	5%	100%	100%	100%	100%	60%	100%	
	10%	100%	100%	100%	100%	60%	100%	
	Average	-18,52	-25,24	-30,20	-32,16	0,56	1,73	
	Absolute Average	18,52	25,24	30,20	32,16	0,56	1,73	
Poland								
% of Observations	1%	100%	100%	100%	100%	4%	39%	
Significant at	5%	100%	100%	100%	100%	9%	60%	
	10%	100%	100%	100%	100%	22%	69%	
	Average	-30,73	-28,75	-33,88	-30,30	0,23	0,71	
	Absolute Average	30,73	28,75	33,88	30,30	0,23	0,71	
Slovakia								
% of Observations	1%	100%	100%	100%	100%	0%	100%	
Significant at	5%	100%	100%	100%	100%	0%	100%	
	10%	100%	100%	100%	100%	0%	100%	
	Average	-22,35	-34,85	-22,24	-34,81	0,11	0,96	
	Absolute Average	22,35	34,85	22,24	34,81	0,11	0,96	
Slovenia								
% of Observations	1%	100%	100%	100%	100%	0%	64%	
Significant at	5%	100%	100%	100%	100%	17%	79%	
	10%	100%	100%	100%	100%	33%	93%	
	Average	-28,19	-30,21	-38,55	-32,87	0,27	0,93	
	Absolute Average	28,19	30,21	38,55	32,87	0,27	0,93	

All calculations were made on natural logarithms of Bloomberg last prices in local currency
Augmented Dickey Fuller (ADF) test, H0: unit root, H1: no unit root (stationary)
Phillips Peron (PP), H0: unit root, H1: no unit root (stationary)
Kwiatkowski, Phillips, Schmidt and Shin (KPSS), H0: no unit root (stationary), H1: unit root

Table 4: *Multiple variance ratio tests*

		T Statistic q=2			T Statistic q=5			T Statistic q=10			T Statistic q=20			Stocks significant at at least one of the above time intervals		
		1999-2003	2004-2008	Z Test	1999-2003	2004-2008	Z Test	1999-2003	2004-2008	Z Test	1999-2003	2004-2008	Z Test	1999-2003	2004-2008	Z Test
Entire Region																
% of Observations Significant at	1%	14%	19%	-0,97	12%	21%	-1,66	7%	19%	-2,62	9%	20%	-2,24	22%	31%	-1,63
	5%	31%	32%	-0,25	26%	32%	-1,12	20%	28%	-1,47	16%	29%	-2,27	41%	44%	-0,38
	10%	38%	38%	-0,04	35%	38%	-0,43	25%	33%	-1,41	25%	37%	-2,03	55%	54%	0,05
Czech Republic																
% of Observations Significant at	1%	0%	14%		0%	0%		0%	0%		0%	0%		0%	14%	
	5%	40%	14%		20%	14%		20%	0%		0%	0%		40%	14%	
	10%	40%	14%		20%	14%		20%	0%		0%	0%		40%	14%	
Estonia																
% of Observations Significant at	1%	40%	25%		40%	0%		20%	0%		20%	13%		60%	38%	
	5%	60%	50%		80%	38%		80%	0%		60%	13%		100%	75%	
	10%	80%	50%		80%	38%		80%	13%		80%	25%		100%	88%	
Hungary																
% of Observations Significant at	1%	13%	13%		13%	13%		0%	0%		13%	0%		25%	13%	
	5%	13%	25%		13%	13%		13%	13%		13%	0%		25%	25%	
	10%	13%	38%		25%	13%		25%	13%		50%	13%		63%	38%	
Latvia																
% of Observations Significant at	1%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
	5%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
	10%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
Lithuania																
% of Observations Significant at	1%	10%	10%		20%	30%		20%	30%		30%	60%		40%	60%	
	5%	30%	40%		30%	40%		50%	50%		40%	70%		60%	70%	
	10%	30%	40%		50%	40%		50%	50%		40%	80%		70%	80%	
Poland																
% of Observations Significant at	1%	15%	22%		11%	25%		5%	25%	-2,98	5%	22%		18%	31%	
	5%	27%	34%		24%	37%		13%	33%	-2,80	13%	33%		35%	45%	
	10%	38%	41%		35%	44%		16%	39%	-2,95	18%	41%		49%	56%	
Slovakia																
% of Observations Significant at	1%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
	5%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
	10%	0%	0%		0%	0%		0%	0%		0%	0%		0%	0%	
Slovenia																
% of Observations Significant at	1%	17%	14%		8%	14%		8%	7%		8%	7%		17%	29%	
	5%	50%	21%		25%	14%		8%	14%		8%	14%		50%	29%	
	10%	50%	29%		25%	21%		25%	21%		17%	21%		58%	43%	

All calculations were made on natural logarithms of Bloomberg last prices in local currency; Sampling intervals (q) are in days

Even at the 0.01 level of significance, the MVR tests generally suggest that many stocks in our dataset do not follow a random walk process. While the percentage of stocks significant for at least one of the q levels is substantially higher for the post-accession dataset than the pre-accession dataset, the z-tests reveal that this is not statistically significant. At the 0.1 level of significance, more than half of all stocks do not conform to a random walk process for at least one of the sampling intervals applied, and the results are very similar for the pre- and post-accession nations. Excluding Czech Republic, Latvia and Slovakia (the small number of stocks listed in these nations makes inferences about them questionable anyway), there is not a large variation amongst the different countries in our dataset, with the results for Poland and the entire region being almost identical.

4.4 Liquidity Controls

Table 5 shows the results from the liquidity controls employed:

The results from using market capitalization as a proxy for liquidity are shown in Table 5 Panel A. For both the pre- and post-accession datasets, smaller capitalized stocks exhibit higher levels of serial correlation. Runs tests are also substantially affected by their market capitalization quintile, with the smaller market capitalization quintile stocks returning a higher proportion of significant results. The ADF and PP tests are both excluded from the table as every stock in our dataset can be considered statistically significant at the 0.01 level and thus there is no variation across any of the liquidity quintiles. For the KPSS tests, the results for the large market capitalization quintile are very similar to those from the small market capitalization quintile, therefore there is nothing to suggest that the KPSS tests is affected by liquidity (as measured by market capitalization). For the MVR tests, portfolio 5 actually has a higher percentage of stocks returning statistically significant results than any of the other four quintiles: lack of liquidity is clearly not distorting results from the MVR tests. Whilst lack of liquidity associated with smaller market capitalization may have distorted some of the tests of serial independence, a substantial number of stocks in the largest market capitalization portfolio still return significant results. Market capitalization does not have any meaningful effect on any of the three unit root tests of the MVR tests.

The results from using average volume divided by shares outstanding as a liquidity control are shown in Table 5 Panel B. For serial correlation, the number of stocks significant at each of the three significance levels we use is actually higher in the most liquid portfolio 5 than in the least liquid portfolio 1. Therefore, there is no indication that lack of liquidity, as measured by average volume divided by shares outstanding, is distorting the serial correlation tests. Whilst the runs tests return the highest percentage of significant results for the lowest-liquidity portfolio 1, there is not a huge amount of variation across the quintiles. In a similar manner to the serial correlation statistic, the percentage of stocks returning significant results for the KPSS tests actually increases as liquidity increases. The MVR tests return very similar results across the five quintiles. It is clear that

Table 5 Panel A: *Liquidity Controls - Market Cap*

		Tests of Serial Independence						Unit Root Tests		Multiple variance ratio tests	
		Serial Correlation T Statistic		Number of Runs		Runs Test		KPSS Test		Stocks significant for at least one of the q sampling intervals	
		2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008
Quintile 1											
Observations %	1%	50%	11%			30%	26%	10%	51%	30%	34%
of Observations	5%	60%	86%			45%	46%	20%	69%	55%	60%
Significant at	10%	65%	89%			50%	63%	20%	80%	75%	69%
	Average			422,70	515,03						
Quintile 2											
Observations %	1%	33%	15%			19%	15%	3%	35%	19%	27%
of Observations	5%	33%	31%			39%	31%	11%	50%	36%	42%
Significant at	10%	42%	77%			42%	38%	19%	54%	53%	54%
	Average			540,03	496,62						
Quintile 3											
Observations %	1%	50%	73%			0%	27%	0%	53%	50%	37%
of Observations	5%	50%	80%			50%	50%	0%	63%	50%	43%
Significant at	10%	50%	90%			50%	53%	0%	70%	50%	57%
	Average			319,00	512,00						
Quintile 4											
Observations %	1%	23%	33%			9%	10%	5%	33%	14%	17%
of Observations	5%	41%	50%			27%	27%	5%	60%	32%	20%
Significant at	10%	41%	50%			45%	50%	23%	77%	36%	37%
	Average			478,77	438,63						
Quintile 5											
Observations %	1%	12%	10%			35%	17%	6%	53%	24%	40%
of Observations	5%	24%	13%			41%	37%	24%	77%	47%	50%
Significant at	10%	24%	20%			53%	37%	47%	77%	59%	53%
	Average			524,47	552,57						

Market capitalization is an average of daily market capitalization taken from Bloomberg in Euros over the period for which the weak form tests for the individual security were calculated.
Stocks are ranked according to their market capitalization in Euros and assigned to quintiles 1 (low) to 5 (high). The results from Tables 2, 3 and 4 are shown for each market capitalization quintile.

Table 5 Panel B: *Liquidity Controls – Average Volume Divided by Shares Outstanding*

		Tests of Serial Independence						Unit Root Tests		Multiple variance ratio tests	
		Serial Correlation T Statistic		Number of Runs		Runs Test		KPSS Test		Stocks significant for at least one of the q sampling intervals	
		2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008
Quintile 1											
Observations %	1%	35%	16%			45%	26%	15%	48%	45%	35%
of Observations	5%	50%	29%			65%	42%	30%	55%	65%	52%
Significant at	10%	50%	71%			70%	58%	40%	55%	80%	65%
	Average			395,35	527,39						
Quintile 2											
Observations %	1%	5%	0%			11%	20%	5%	53%	16%	37%
of Observations	5%	16%	7%			26%	30%	16%	73%	32%	53%
Significant at	10%	16%	10%			47%	40%	47%	73%	37%	53%
	Average			530,21	477,07						
Quintile 3											
Observations %	1%	84%	37%			21%	7%	0%	37%	11%	20%
of Observations	5%	95%	57%			37%	30%	11%	60%	37%	23%
Significant at	10%	95%	60%			47%	47%	21%	80%	42%	40%
	Average			527,89	497,43						
Quintile 4											
Observations %	1%	32%	7%			11%	23%	0%	43%	11%	27%
of Observations	5%	32%	87%			32%	43%	5%	67%	47%	53%
Significant at	10%	42%	87%			37%	53%	5%	80%	58%	63%
	Average			595,89	513,03						
Quintile 5											
Observations %	1%	0%	83%			20%	20%	5%	47%	25%	37%
of Observations	5%	5%	90%			30%	47%	5%	67%	25%	37%
Significant at	10%	15%	100%			30%	47%	10%	73%	55%	50%
	Average			432,45	501,97						

Both average volume and shares outstanding were calculated as average of daily observations taken from Bloomberg over the period for which the weak form tests for the individual security were calculated.

Stocks are ranked according to average volume divided by shares outstanding and assigned to quintiles 1 (low) to 5 (high). The results from Tables 2, 3 and 4 are shown for each average volume divided by shares outstanding quintile.

Table 5 Panel C: *Liquidity Controls – Bid-Ask Spread*

		Tests of Serial Independence						Unit Root Tests		Multiple variance ratio tests	
		Serial Correlation T Statistic		Number of Runs		Runs Test		KPSS Test		Stocks significant for at least one of the q sampling intervals	
		2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008	2000-2004	2004-2008
Quintile 1											
Observations %	1%	0%	58%			13%	10%	0%	45%	21%	26%
of Observations	5%	4%	74%			33%	26%	4%	65%	33%	29%
Significant at	10%	17%	74%			38%	35%	8%	77%	50%	42%
	Average			530,96	521,19						
Quintile 2											
Observations %	1%	60%	60%			27%	20%	7%	43%	27%	30%
of Observations	5%	60%	73%			40%	47%	7%	67%	47%	37%
Significant at	10%	60%	80%			40%	53%	13%	80%	53%	57%
	Average			358,67	452,07						
Quintile 3											
Observations %	1%	84%	0%			32%	20%	5%	42%	26%	28%
of Observations	5%	89%	50%			47%	40%	21%	54%	53%	48%
Significant at	10%	89%	76%			58%	56%	26%	62%	63%	58%
	Average			542,16	502,82						
Quintile 4											
Observations %	1%	22%	50%			22%	30%	9%	50%	17%	30%
of Observations	5%	39%	70%			39%	60%	17%	60%	39%	60%
Significant at	10%	43%	80%			48%	80%	30%	60%	52%	70%
	Average			501,30	543,50						
Quintile 5											
Observations %	1%	0%	7%			19%	23%	6%	53%	19%	43%
of Observations	5%	13%	13%			31%	33%	19%	80%	38%	53%
Significant at	10%	13%	20%			50%	37%	50%	80%	56%	53%
	Average			501,75	524,63						

Bid-ask spread and last price is an average of daily market capitalization taken from Bloomberg in Euros over the period for which the weak form tests for the individual security were calculated. The bid-ask spread was divided by the last price in order to obtain a percentage measure.
Stocks are ranked according to their Bid-ask spread and assigned to quintiles 1 (low) to 5 (high). The results from Tables 2, 3 and 4 are shown for each Bid-ask spread quintile.

liquidity as measured by average volume divided by shares outstanding is not distorting any of the results from these tests.

The results from using the bid-ask spread as a liquidity measure are shown in Table 5 Panel C. Note that, unlike the market capitalization and average volume divided by shares outstanding liquidity controls, higher bid-ask spreads are associated with lack of liquidity. Thus portfolio 1 contains stocks with the lowest bid-ask spreads and highest liquidity. For the serial correlation tests, quintile 1 returns a greater percentage of stocks with statistically significant results than quintile 5; therefore, lack of liquidity is not distorting these results. For the runs tests, the extreme bid-ask portfolios 1 and 5 return the lowest percentage of statistically significant results for the runs test; the median quintile 3 returns the highest percentage of statistically significant results: runs test results are not affected by liquidity as measured by bid-ask spread. The KPSS tests return a marginally higher percentage of statistically significant results for quintile 5, but the results are largely consistent across quintiles. The numbers of stocks returning statistically significant results from the MVR tests increases for the wider bid-ask quintiles, but the lower bid-ask quintiles still return a substantial number of statistically significant results. We can thus conclude that bid-ask spread is not distorting the results of our WFME tests.

Hence from the liquidity tests employed it is clear that the apparent weak-form inefficiencies highlighted by the WFME tests cannot be entirely explained away by liquidity issues. While liquidity may have some explanatory power for some of the tests, it is clear that lack of liquidity is not creating a spurious sense of weak form inefficiency.

5. CONCLUDING REMARKS

The tests employed are in broad agreement: the stock markets of the EE EU nations are not WFME, nor have they become more efficient since EU accession. This contravenes the expectations of many academics who expected these markets to become more efficient and leads us to hypothesize that the inefficiencies will remain for years to come. Many researchers suggested that the passage of time would allow market participants to gain experience and make markets more efficient, however as this has not happened after nearly 20 years of operating, there is no reason to presume that it ever will. Some earlier studies argued that the process of EU integration will improve market efficiency, however our dataset covers the 5 years following EU accession and these markets are still inefficient. Finally, some suggested that the small size of the stock markets of the EE EU made them inefficient, however the number of stocks listed on the Warsaw Stock Exchange has increased to make the number of listed shares comparable to the exchanges of the pre-enlargement EU nations, yet our results show that the Polish stock market is no more efficient than the rest of the EE EU region. The reasons researchers gave for expecting the stock markets of the EE EU nations to become WFME have clearly not materialized: given this, it is hard to see what catalyst can drive these markets to become efficient. Therefore we expect the stock markets of the EE EU countries to remain weak form inefficient for the foreseeable future.

Given our tests incorporate two sub periods and indicate no improvement in the level of WFME in the EE EU nations, our view is that these stock markets will take a significant amount of time to show any meaningful improvement in WFME. This has substantial ramifications. While the issue is most obviously of interest to researchers and market participants engaged in technical analysis and trading models, lack of WFME also has much more important implications for corporate financial decisions and the development of the broader economy. There is a well-established link between pricing efficiency and the efficient allocation of capital; consequently, the absence of WFME in the EE EU nations may impair corporate finance decisions and prevent companies from attaining an optimal capital structure. Even more importantly, the link between the pricing efficiency of a country's stock market and the nation's overall economic development and the possibility that the availability of stock market financing can enhance economic growth means that it is clear that WFME has significant ramifications not just for a country's capital market but also its overall economic development. Furthermore, WFME is of particular importance in the EE EU countries: an efficient capital market can facilitate the ongoing privatization process; as these nations are aiming for economic convergence with the pre-enlargement EU nations, the stock market clearly has a large role to play here; finally, as Worthington and Higgs (2004) suggest, the absence or presence of WFME in Europe's developing markets is an important consideration in the debate about what technological and regulatory reform is necessary or even whether the region's exchanges should merge.

In this paper we focussed on establishing whether stocks listed in the EE EU conform with WFME. Although we do not offer a concrete explanation of the causes of WFME in the region's stock markets, previous research such as Griffin et al (2010) focused on transaction costs and information flow as the drivers of WFME. Thus policy makers may consider improving information flow for example through access to real time prices or encouraging research coverage from a wide range of analysts, alternatively lowing transaction costs may offer a solution.

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