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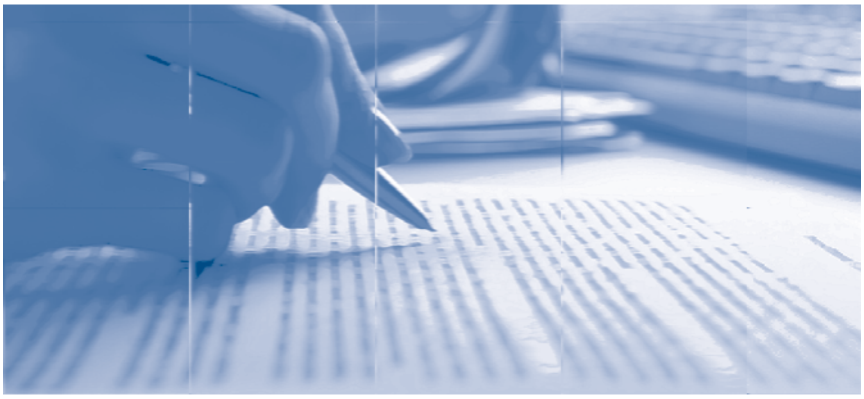

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How much random does European Union walk? A time-varying long memory analysis

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Benjamin M. Tabak[‡]

Abstract

This paper proposes a new efficiency index to model time-varying inefficiency in stock markets. We focus on European stock markets and show that they have different degrees of time-varying efficiency. We observe that the 2008 global financial crisis has had an adverse effect on almost all EU stock markets. However, the Eurozone sovereign debt crisis has had a significant adverse effect only on the markets in France, Spain and Greece. For the late members, joining EU does not have a uniform effect on stock market efficiency. Our results have important implications for policy makers, investors, risk managers and academics.

Keywords: Long memory; European Union; Stock Market Efficiency; Generalized Hurst Exponent
JEL Classification: C00, C1, G01, G14, G15, N24

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1 Introduction

Market efficiency has been widely discussed in financial literature. According to the weak form of Efficient Market Hypothesis (EMH) (Fama, 1970), stock prices follow a random walk, a term to denote the logic asserting that tomorrow's price changes only reflect tomorrow's news where news is assumed to be unpredictable hence price changes must be random (Malkiel, 2003). However, as far as financial markets are concerned, the notion of long memory was shown to exist in asset returns first by Mandelbort (1971) and then by many others (See Fama and French (1988); Lo and Mackinlay (1988); Poterba and Summers (1988); Brock et al. (1992); Cochran et al. (1993)).

The presence of long memory brings out several problems: The investors' preferred investment horizon becomes a risk factor (Mandelbort, 1997); the methods used to price financial derivatives (such as the Black and Scholes (1973) model) may no longer be valid;[1] the usual tests based on the Capital Asset Pricing Model and Arbitrage Pricing Theory (Black et al., 1972) cannot be applied to series with long memory.[2]

This paper aims to compare the efficiency of all stock markets in European Union (EU) after the introduction of the Euro.[3] This comparison is essential in many ways, for example; since not all EU members use Euro as their currency, it is an important question to answer if such a situation made any difference on the stock market efficiency in the last decade. A similar question arises due to the fact that some of the countries in our analysis joined EU or started to use Euro later than others in the time interval of our study. Furthermore, the study time line includes two major crisis; namely the 2008 global financial crisis and the Eurozone sovereign debt crisis.

In 2008, the US experienced a major financial crisis leading to one of the most serious recessions in history. The crisis spread to many foreign nations, especially in Europe, resulting in a global economic crisis. The crisis has had further developments in countries in Europe with weak fiscal discipline, leading to the European debt crisis. Six of the region's countries; Greece, Portugal, Ireland, Italy, Spain, Cyprus, have struggled to fully pay back their bondholders. Although these six are seen as the most problematic, their possible default has far-reaching consequences beyond their borders. This study will also show the effects these crises have had on the efficiency of European stock markets.

[1]Jamdee and Los (2007) demonstrates how long memory phenomena can change European option values compared to the Black-Scholes model assumptions.

[2]Mandelbort (1971) notes that the arrival of new information can not be fully arbitraged away in the presence of long memory and asset pricing with martingale models cannot be obtained from arbitrage.

[3]The Euro is the second largest reserve currency as well as the second most traded currency in the world after the United States dollar.

This is the first study that compares relative efficiency of all stock markets in EU and we use the Hurst exponent in that purpose. Many previous weak-form EMH studies assume a fixed level of market efficiency throughout the entire estimation period. It is incorrect to assume that the market is perpetually in an equilibrium state (Lo, 2004, 2005). Hence, instead of regular static approaches, we use a time-varying approach to see the dynamics of the efficiency. Moreover, instead of the popular R/S (Hurst, 1951) and modified R/S (Lo, 1991) statistics approach, we use the generalized Hurst exponent (GHE) introduced by Barabasi and Vicsek (1991). It combines sensitivity to any type of dependence in the data and simplicity. Furthermore, since it does not deal with maxima and minima, it is less sensitive to outliers than the popular R/S statistics (Barabasi and Vicsek, 1991; Di Matteo et al., 2005). Besides, it is a stylized fact that the stock returns are not normally distributed and are heavy-tailed. Barunik and Kristoufek (2010) studies how the sampling properties of the Hurst exponent estimate change with fat tails by comparing the R/S analysis, multifractal detrended fluctuation analysis, detrending moving average and the generalized Hurst exponent approach in estimating the Hurst exponent on independent series with different heavy tails. They show that GHE is robust to heavy tails in the underlying process and provides the lowest variance.

Finally, we contribute to the literature by introducing a time-varying efficiency index that could be useful especially in analyzing the effects of exogenous events on the efficiency level.

The structure of the paper is as follows: Section 2 gives a brief literature review on the efficiency of European stock markets. Section 3 explains the methodology used in this study. Section 4 presents the data and the results. Finally section 5 includes some discussion and offers a brief conclusion.

2 Review of past studies on the efficiency of European stock markets

The efficiency of stock markets has been a subject of much attention in the empirical finance literature.[4] The literature that focus on European stock markets has employed various methodologies. However, the literature provides mixed evidence. Cheung and Lai (1995) found no evidence of long memory in major European stock markets using a modified R/S test and a fractional differencing test. Using the modified R/S statistic, Jacobsen (1996) shows that none of the return series of indexes of five major European countries exhibits long memory. Lux (1996), applying three different concepts for the identification of long memory effects, virtually found no evidence of such behavior in German stock

[4]For example see Sadique and Silvapule (2001); Cajueiro and Tabak (2004, 2007, 2008); Kim and Shamsuddin (2008); Lim and Kim (2011); Goddard and Onali (2012); Spierdijk et al. (2012); Sensoy (2013) for international stock markets.

market returns. Dockery and Kavussanos (1996) performs unit root tests using panel data to investigate empirically stock price efficiency of the Athens stock market and their Wald test statistics reject the random walk hypothesis for stock prices. However, using time-varying global Hurst exponents, Cajueiro et al. (2009) show that after the financial liberalization in Greece, stock market efficiency has significantly improved in time.

Booth and Koutmos (1998) studies four major European stock markets by modeling their returns as conditionally heteroskedastic processes with time dependent serial correlation. Their evidence suggests that returns in these markets are non-linearly dependent on their past history. Vir (2000) examines the long memory property in Finnish stock market by various alternative test procedures. The results give some evidence on long memory but do not overwhelmingly support their existence in the Finnish stock market. Areal and Armada (2002) find tendencies towards mean aversion and mean reversion in Portuguese stock market using several methodologies, however they notice that results are very sensitive to the methodology used and the significance tests performed. Smith and Ryoo (2003) test the assertion that stock prices of five European emerging markets; Greece, Hungary, Poland, Portugal and Turkey, follow a random walk using the multiple variance ratio test. The assertion is rejected in all cases except Turkish stock market. Fifield et al. (2005) test the validity of the weak form of EMH for a selection of 11 European stock markets. Their findings indicate that the emerging markets included in their study are informationally inefficient; they display some degree of predictability in their returns, although the developed markets do not.

Lately, Hurst exponent became very popular in analyzing the stock market efficiency. Cajueiro and Tabak (2006) present empirical evidence of short and long-run predictability in stock returns for European transition economies using Hurst exponent. Furthermore, they find that this long-range dependence is strongly time-varying. With a similar methodology, Onali and Goddard (2009) test for random walk behavior in the Italian stock market. They reveal that departure from random walk behavior is statistically significant on standard criteria. Later in another study, Onali and Goddard (2011) analyze long memory in the returns of eight European stock market indexes and find strong evidence of long memory for the stock market of Czech Republic, and a weaker evidence for the stock markets of Spain and Switzerland.

Borges (2010) tests the weak form EMH on stock market indexes of UK, France, Germany, Spain, Greece and Portugal using a runs test and joint variance ratio tests. This hypothesis is rejected in Portugal, Greece, France and UK, however it is not rejected in Germany and Spain. Smith (2012) tests for random walk behavior of 15 European stock markets with a rolling window variance ratio tests. He finds that the most efficient are the Turkish, UK, Hungarian and Polish markets and the least efficient are the Ukrainian, Maltese and Estonian stock markets. Furthermore, the 2008 financial crisis coincides with return predictability in the Croatian, Hungarian, Polish, Portuguese, Slovakian and UK stock markets. However, the crisis had little effect on weak form efficiency in stock markets of Greece, Latvia, Romania, Russia and Turkey.

Based on the above studies, one could state that efficiency analyzes for European stock markets do not come to a unified conclusion and the results vary in time.

3 Methodology

Several methods have been proposed to analyze the long memory in time series[5] and the literature review shows that the two most common techniques used for European stock markets are the modified R/S analysis and the variance ratio tests. However, in this study we will follow a different methodology. We are interested in the degree of long memory of a given stochastic process $S(t)$ with $t = (1, 2, ..., \Delta t)$ defined over a time window Δt with unitary time steps and we use $H(q)$ as a measure of long memory.[6] It is a generalization of the approach proposed by Hurst (1951) and it may be evaluated using the q^{th}-order moments of the distribution of increments, which is a good characterization of the statistical evolution of $S(t)$ (Barabasi and Vicsek, 1991),

$$K_q(\tau) = \frac{< |S(t+\tau) - S(t)|^q >}{< |S(t)|^q >} \tag{1}$$

where τ can vary between 1 and τ_{max} and $< ... >$ denotes the sample average over the time window.[7] $H(q)$ is then defined for each time scale τ and each parameter q as

$$K_q(\tau) \propto \tau^{qH(q)} \tag{2}$$

[5]See Taqqu et al. (1995) for a survey of these methods.

[6]In financial applications, $S(t)$ is the log-prices for stock markets.

[7]For $q = 1$, eq.(1) describes the scaling behavior of the absolute increments and it is expected to be closely related to the original Hurst exponent which is indeed associated with the scaling of the absolute spread in the increments (Di Matteo, 2007). Therefore, in this work, we focus on the case $q = 1$. For $q = 2$, $K_q(\tau)$ is proportional to the autocorrelation function $C(t, \tau) =< S(t+\tau)S(t) >$.

$H(q)$ is computed through a linear least squares fitting[8] using a set of values corresponding to different values of τ_{max} in eq. (1).[9] For any value of q, $H(q) = 0.5$ means that $S(t)$ does not exhibit long memory, while $H(q) > 0.5$ and $H(q) < 0.5$ implies that $S(t)$ is persistent and mean-reverting respectively.[10]

3.1 Calculation of the standard errors

The standard errors of the $H(1)$ estimates are found by employing a pre-whitening and post-blackening bootstrap approach of Grau-Carles (2005) that also previously used by Cajueiro and Tabak (2008, 2010) and Souza et al. (2008). The methodology can be summarized as follows:

1. Obtain the log-returns $r(t)$ from log-prices.
2. Do the pre-whitening by estimating an $AR(p)$ model for log-returns with p sufficiently high (we take p from 1 to 30). The order of the AR is estimated through the Akaike information criteria.
3. Obtain the residuals $\epsilon(t)$ of the AR model from the historical sequence.
4. Obtain the simulated innovations by bootstrapping $\epsilon(t)$ using the circular block bootstrap (Politis and Romano, 1992), where the choice of block length is given by the rule provided in Politis and White (2004).[11]
5. The post-blackening is made, adding the innovations series generated by bootstrap to the model whose parameters were generated in the pre-whitening, to obtain the synthetic log-return series.
6. The synthetic log-prices are recovered recursively from bootstrap samples of synthetic log-returns.
7. For each synthetic log-prices, the $H_b(1)$ is estimated.

We run 100 bootstrap samples and estimate $H(1)$ for them. Then the standard deviation $S(H_b(1))$ of these estimates taken as a proxy for the standard error of generalized Hurst exponents. At the end

[8] Observe that relation (2) leads to $\ln K_q(\tau) = qH(q) \ln \tau + C$.

[9] In the spirit of Di Matteo et al. (2005), we let τ_{max} vary between 5 to 19 days.

[10] Processes with a scaling behavior of (2) may be divided into two classes: (i) unifractal processes that $H(q)$ is independent of q i.e. $H(q) = H$ or (ii) multifractal processes that $H(q)$ is not constant and each moment scales with a different exponent. Previous researches (Xu and Gencay, 2003; Cajueiro and Tabak, 2004, 2005; Di Matteo et al., 2005) show that financial time series exhibit multifractal scaling behavior. Calvet and Fisher (2002) explore the implications of multifractality and suggest new models for forecasting which are competitors to GARCH models.

[11] We use the rule corrected in 2009.

of the process, the Wald statistic[12] is given by $W = (\frac{H(1)-0.5}{S(H_b(1))})^2$ and it tests the null hypothesis of *long memory does not exist*.

4 Data and Results

We consider daily prices of all stock markets in the European Union (current members) after the introduction of Euro (covers a time period between 02/01/1999 and 25/02/2013). This condition gives us 27 markets to consider which are listed in Table 1 in the A.

4.1 Dynamic approach and an efficiency ranking

We use a rolling sample approach, therefore we do not have to use a strict cut off date which is usually subject to criticism. Even when an important event occurs such as a financial crisis, it may take a long time for its full effect to take place. Similarly, possible structural breaks must be taken into account when analyzing financial time series, since arbitrarily chosen sub-samples or non-overlapping intervals could not capture this dynamic.[13]

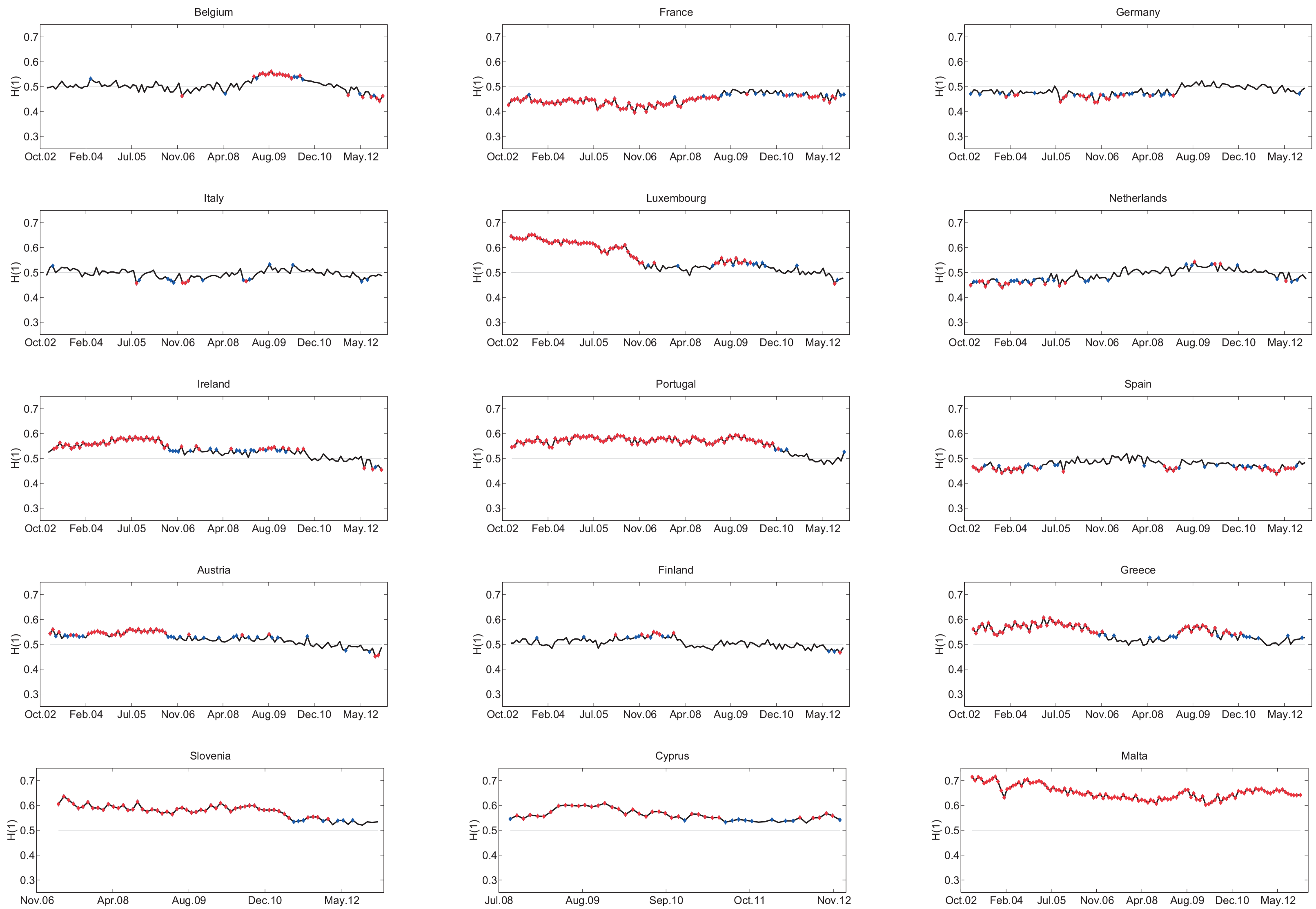
Recent studies using rolling window approach revealed that market efficiency evolves over time. In order to see if this is the case, we choose a 4 year (1008 observations) time-window (that shift 22 points at a time) since it corresponds to the duration of political cycles in most of the countries under our study and it is large enough to provide satisfactory statistical significance.

We use an approach similar to those of Zunino et al. (2007); Lim (2007) and Lim et al. (2008): For each window, we calculate $H(1)$ and its standard errors to obtain the Wald statistic W. Then, we call a window *significant* if the null hypothesis of efficiency is rejected (naturally, we call it *insignificant* if efficiency is not rejected). The rolling window approach reveals how often the long memory hypothesis is rejected by the selected test statistic, and hence the percentage of sub-samples with an insignificant test statistic (which we call *efficiency ratio*) can be used to compare the relative efficiency of our 27 stock markets (See Table 1 for a relative efficiency ranking).

For all stock markets, Figure 1 presents the time-varying $H(1)$ with a black curve (The descriptive statistics of the time-varying $H(1)$ can be found in Table 2 in the A). Figure 1 also displays the dynamic rejection status of efficiency by blue and red markers denoting the rejection of efficiency at 5% and 1% significance levels respectively.

[12]The W has a χ_1^2 distribution (Tabak and Cajueiro, 2006; Cajueiro and Tabak, 2008; Souza et al., 2008).

[13]There is an expanding literature tracking the evolution of market efficiency over time by means of a time-varying parameter model or a rolling estimation window. For details, see the survey paper by Lim and Brooks (2011).



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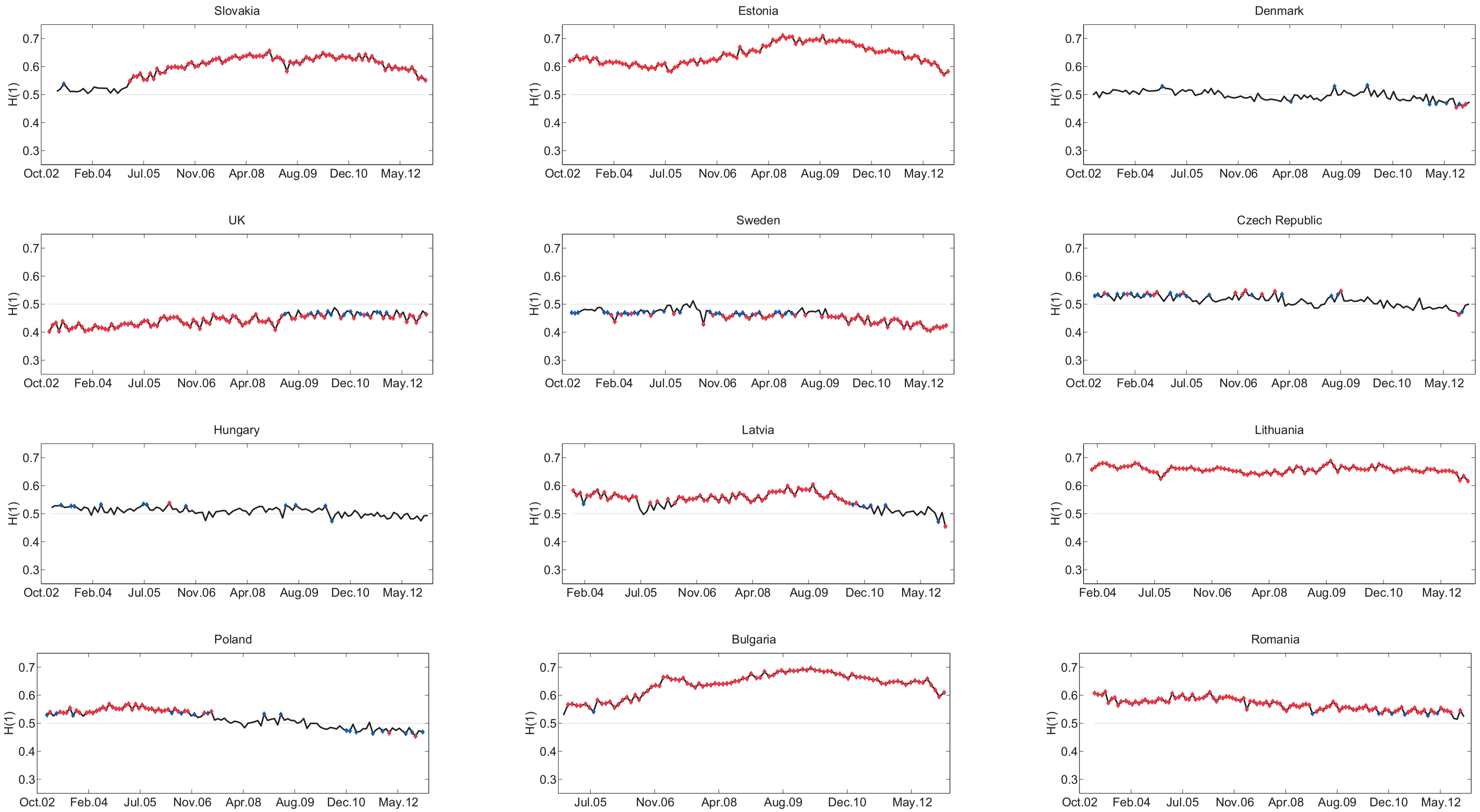

Figure 1: Black curves are the time-varying $H(1)$ of stock markets in European Union obtained from a 4 year length rolling window. Blue and red markers denote the rejection of efficiency at 5% and 1% significance levels respectively.

Table 1: Efficiency ranking of stock markets based on analysis with a rolling window of 4 year length

Market	Sig. windows (5%)	Sig. windows (1%)	Total windows	Eff. ratio (5%)	Eff. ratio (1%)
Denmark	11	3	115	90.4%	97.4%
Hungary	12	1	115	89.6%	99.1%
Italy	17	5	117	85.5%	95.7%
Finland	18	8	115	84.4%	93.0%
Belgium	29	21	118	75.4%	82.2%
Czech Republic	32	13	115	72.2%	88.7%
Germany	37	19	117	68.4%	83.8%
Netherlands	40	18	118	66.1%	84.8%
Spain	52	35	116	55.2%	69.8%
Poland	58	41	115	49.6%	64.4%
Austria	58	36	113	48.7%	68.1%
Luxembourg	70	59	115	39.1%	48.7%
Ireland	73	56	116	37.1%	51.7%
Greece	78	62	114	31.6%	45.6%
Latvia	78	72	105	25.7%	31.4%
Sweden	86	60	115	25.2%	47.8%
Slovakia	90	89	109	17.4%	18.4%
Portugal	97	93	117	17.1%	20.5%
France	99	83	118	16.1%	29.7%
Slovenia	59	52	66	10.6%	21.2%
UK	106	94	116	8.6%	19.0%
Cyprus	46	35	50	8.0%	30.0%
Romania	109	103	112	2.7%	8.0%
Bulgaria	92	91	93	1.1%	2.2%
Malta	113	113	113	0.0%	0.0%
Estonia	116	116	116	0.0%	0.0%
Lithuania	102	102	102	0.0%	0.0%

1. A significant window (α%) is a window where market efficiency is rejected at α% significance level.
2. Efficiency ratio is calculated by dividing the number of insignificant windows by total number of windows.
3. Ordering from top to down is in descending order of efficiency based on the efficiency ratio (5%).

First thing to notice in Figure 1 is that all stock markets have different degrees of time-varying efficiency. According to Table 1, the group of most efficient markets include Denmark, Hungary, Italy and Finland. For all these markets, the efficiency ratio is above 80% at both 0.05 and 0.01 significance levels. These are followed by a second group of markets consisting of Belgium, Czech Republic, Germany and Netherlands. For this group, the efficiency ratio is above 60% at both 0.05 and 0.01 significance levels. A thing to notice is that for both groups, 3/4 of the markets are developed i.e. only Hungary in group one and Czech Republic in group two can be considered as emerging markets. On the other hand, the group of least efficient markets include Romania, Bulgaria, Malta, Estonia and Lithuania. At both 0.05 and 0.01 significance levels, efficiency ratios are below 10% for these markets. The findings give us evidence for developed markets being more efficient than emerging markets in the EU which is in parallel with findings of Di Matteo et al. (2005) and Fifield et al. (2005). However, an exceptional case exists: While being Europe's two of the largest financial markets, France and UK have unexpected performances in terms of efficiency with efficiency ratios below 30% at both 0.05 and 0.01 significance levels. This situation supports the findings of Borges (2010) and contradicts with those of Smith (2012) who states that UK is one of the most efficient markets in the Europe.

As mentioned before, time interval of our study includes the 2008 global financial crisis and the Eurozone sovereign debt crisis. The time-varying $H(1)$s in Figure 1 tell us that stock market efficiency reacts to the 2008 crisis basically in one of the following ways.

1. Efficiency is adversely affected but recovers in a very short time interval.
2. Efficiency is adversely affected then recovers, however this recovery time can take up to 3-24 months.
3. Efficiency is adversely affected and a recovery is not observed.

Stock markets of Germany, Italy, Netherlands, Spain, Austria, Denmark, Czech Republic, Hungary and Poland belong to first group while stock markets of Belgium, Luxembourg, Ireland, Portugal, Greece and Latvia belong to second one. The third group consists of Malta, Slovakia, Estonia, UK, Sweden, Lithuania, Bulgaria and Romania (we could not strictly categorize the few remaining markets). Contents of the groups reveal a direct relationship between market maturity and the recovery speed of a market in terms of efficiency. One thing to notice is that Hungary, Poland, Czech Republic, UK and Sweden do not use Euro which may suggest that not using Euro could be advantageous for emerging markets and disadvantageous for developed markets in terms of efficiency during a financial crisis. On the other hand Denmark, a developed market but does not belong to Eurozone, is one of the most efficient markets among EU members (both during the 2008 crisis and all time period) hence we could not obtain strict conclusions.

During the sovereign debt crisis (that appeared around mid-2010), the stock market efficiency do not seem to be effected as seriously as it did in the 2008 crisis. Indeed, the obvious adverse effects are only seen in France, Spain and Greece. No serious effect is observed in the other problematic countries Portugal, Ireland and Italy. Moreover, Italy is one of the most efficient stock markets during this time period, and at the same time convergence to efficiency is observed in the markets of Ireland and Portugal.

Another important observation is the convergence of markets in Poland, Czech Republic, Latvia towards efficiency after joining EU in 2004. While this behavior was permanent in Poland and Czech Republic, it was temporary for Latvia. Such a convergence is not observed at all in other late members of EU; Malta, Slovakia, Estonia, Lithuania, Romania and Bulgaria. Furthermore, stock market of Slovakia diverges from efficiency after a short time from joining EU. These different outcomes show that joining EU does not have the same qualitative effect on stock market efficiency.

With a similar approach we may hope to observe the effects of adopting Euro as a currency on stock market efficiency: Slovenia, Cyprus, Malta, Slovakia and Estonia adopted Euro as their currency between 2007-2011 however this time interval coincides with the two major crisis, thus the time series is contaminated by these events.

An explanation for the different impact on European stock markets is that there may be differences in market microstructure. In some countries institutional investors may play an important role and if they trade on information stock markets could become more efficient. Furthermore, European global investors may be targeting specific countries rather than all of them to construct a diversified global portfolio. In some countries it can be easier to invest either due to the market size, or to local regulation. These differences can help explain the changes in efficiency over time and whether specific countries will converge towards more efficient markets.

4.2 Robustness check

The numerical stability of the estimation of $H(1)$ was well studied previously by Di Matteo et al. (2003, 2005) and Di Matteo (2007) by comparing theoretical Hurst exponents with the results of Monte Carlo simulations using different random number generators. In this part, we test the robustness of our standard errors using the Jackknife method (Kunsch, 1989) following the steps of Di Matteo et al. (2005). For each stock market, considering the whole time period, we take out randomly 10% of the sample, calculate $H(1)$ and iterate this procedure 10 times where each time we take out the data which were not taken out previously. We observe that the mean value of $H(1)$s obtained from the Jackknife sample is very close to the original $H(1)$ estimate. Also 75% of the time, max and min values of $H(1)$ obtained from Jackknifed samples stay in the interval defined by $H(1)\pm$standard errors. Furthermore, when we redo this Jackknife procedure by taking out 5% of the sample at a time, this ratio goes up to 85% (See Figure 2 for the detailed results).[14] These ratios are considered to be successful if we take into account that we have two major crisis in the sample period.

On the other hand, in studies with a rolling window, window length can be a controversial subject. In order to see if our efficiency ranking is robust, we repeat our study with a 2 year (504 observations) time-window that shift 22 points at a time. The new ranking is given in Table 3 in the A and it is consistent with our previous ranking.[15]

4.3 A time-varying efficiency index

While approaches as in Figure 1 are very handy in analyzing the qualitative changes in time-varying stock market efficiency, a quantitative measure could be useful for further research. In that manner, we introduce an efficiency index. First idea was to construct an index that at any given time t, it would display the ratio of insignificant windows up to time t to total windows up to time t. However such construction gives equal weight to each window and eventually makes it difficult to observe the late impacts when the time interval gets larger.

Thus, we construct a modified model as follows: For a stock market, suppose we have a total number of N windows and t is a time variable taking values from the set $\{1, 2, ..., N\}$. Let E_t be a $1 \times t$ vector, where the i^{th} column of E_t is 1 if efficiency is not rejected in the i^{th} window, and 0 otherwise. As easily understood, size of E_t increases by one column at each time step. Now, let P_t be a $1 \times t$ vector such that for any given t, the k^{th} column of P_t is $1/\sqrt{(t-k+1)}$ where $k \in \{1, 2, .., t\}$. Then the time-varying efficiency index is constructed as the following,

$$\textit{efficiency index}(t) = \frac{E_t \cdot P_t}{I_t \cdot P_t} \tag{3}$$

where I_t is the $1 \times t$ identity vector and "$\cdot$" is the vector inner product.

To put it in a more conventional way, at any given time t, *efficiency index*(t) measures a weighted ratio of insignificant windows over total windows up to time t where the largest weight is given to the latest efficiency status, and the past weights decay as a power law. Hence, the past is never forgotten. However, the latest status mostly characterizes the index value. By construction, efficiency index can

[14]The $H(1)$ estimates in Figure 2 together with the median values in Table 2 reveal that while emerging markets are persistent, developed markets are mean-reverting in the union.

[15]The ranking is still consistent even with a 1 year length rolling window. For space saving purposes, data is not presented here however, all of it can be obtained upon request.

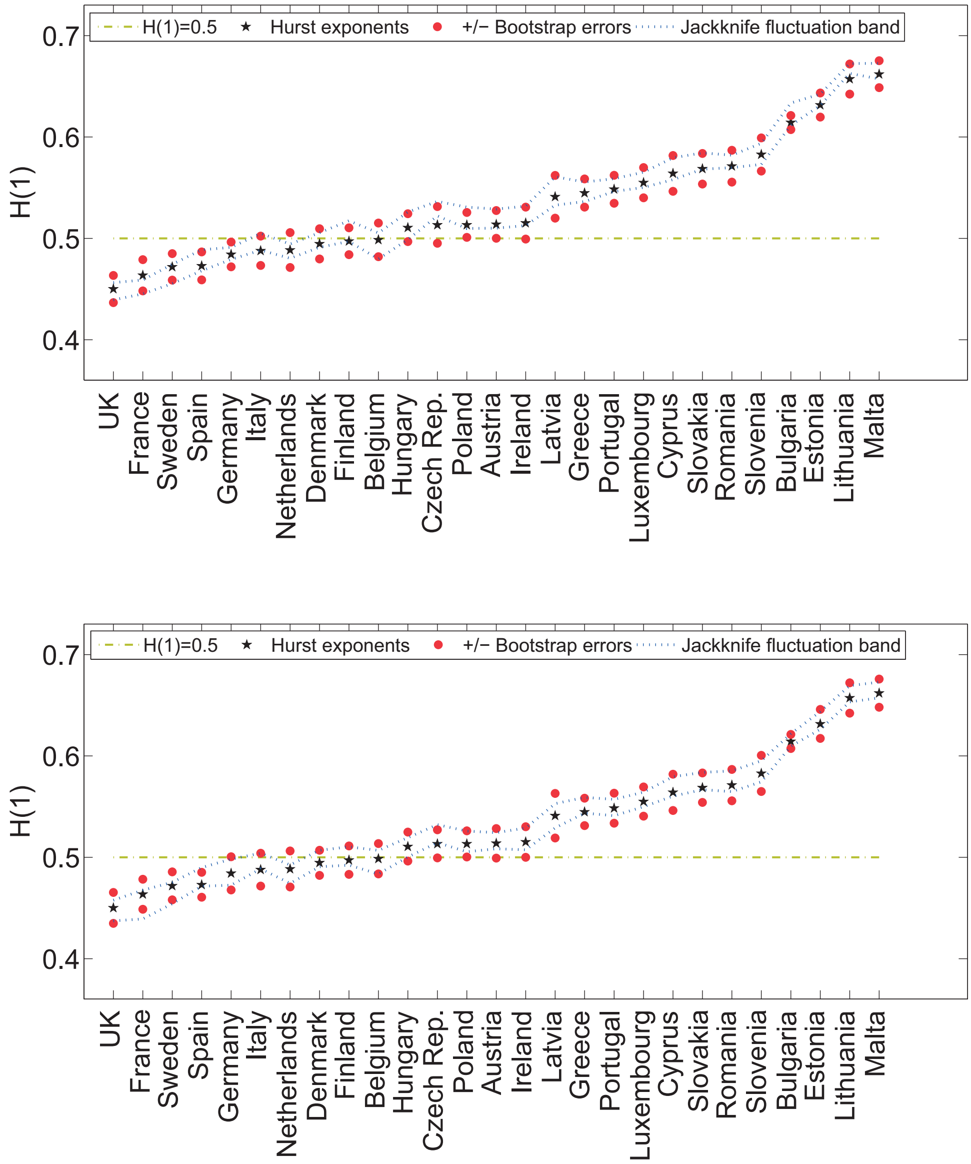

Figure 2: $H(1)$ and $\pm$standard errors together with Jackknife fluctuation band (see upper sub-figure for the Jackknife with a 10% out of sample procedure and lower sub-figure for the 5% out of sample procedure) and the efficiency line $H(1) = 0.5$.

Note: For the 10% out of sample Jackknife procedure, Jackknife fluctuation band stays within the $H(1)\pm$standard errors 75% of the time. For the 5% out of sample case, Jackknife fluctuation band stays within the $H(1)\pm$standard errors 85% of the time. Figure 2 also reveals that while emerging markets are persistent, developed markets are mean-reverting.

take values between 0% and 100% where the previous and the latter correspond to complete inefficiency and complete efficiency respectively.

For each stock market, efficiency indexes are given in Figure 3. As of February 2013, the highest five efficiency index values are as follows;[16] Hungary: 92.5%, Italy: 86.8%, Finland: 83.0% and Denmark: 81.4%. The rest is below 80%.[17] The conclusions we obtained in the previous section can be observed in Figure 3 easily.

5 Conclusion

As much as being a vital concept, market efficiency has been a controversial subject for a lot of academicians and practitioners. Moreover, it is not easy to validate it qualitatively nor to measure it quantitatively. Bearing this fact in mind, this paper investigates the long memory in stock markets in the EU after the introduction of Euro by using generalized Hurst exponent with a rolling window approach. The major findings of the study are summarized as follows. First, all stock markets have different degrees of time-varying long memory. Our dynamic approach reveals that the most efficient stock markets belong to Denmark, Hungary, Italy and Finland while the least efficient ones are in Lithuania, Estonia, Malta and Bulgaria. The empirical evidence shows that market efficiency is positively related with the market maturity, however an exceptional case exists for the stock markets of the UK and France which are found to be relatively inefficient compared to mid-sized markets of EU.

The literature on random walk behavior has found evidence that long-term autocorrelations are negative. Therefore, stock market returns are mean reverting in the long run. This implies that Hurst exponents should be below the 0.5 threshold. However, in several countries we observe Hurst exponents consistently above 0.5 which implies market aversion and persistent behavior. This suggests, that in some stock markets there seems to be prolonged periods with prices deviating from fundamentals. This phenomena can be due to some sort of irrational behavior or due to market microstructure issues. Further research could exploit these issues in depth to gain a better understanding of the deviations from market efficiency.

The studied time line includes two major crisis namely; the 2008 global financial crisis and the Eurozone sovereign debt crisis. Our dynamic approach reveals that while the 2008 crisis has an adverse effect on all stock markets of EU in terms of efficiency, the effect of sovereign debt crisis is limited to

[16]Where significance level is taken to be 0.05 for the rejection of efficiency in a window. See the blue curves in Figure 3.

[17]If the significance level is taken to be 0.01 in the same case, the highest efficiency index values as of February 2013 are Hungary: 99.4%, Italy: 97.0%, Finland: 92.2%, Denmark: 91.4%, Czech Republic: 90.7%, Germany: 89.1% and Netherlands: 89.0%. The rest is below 80%. See the red curves in Figure 3.

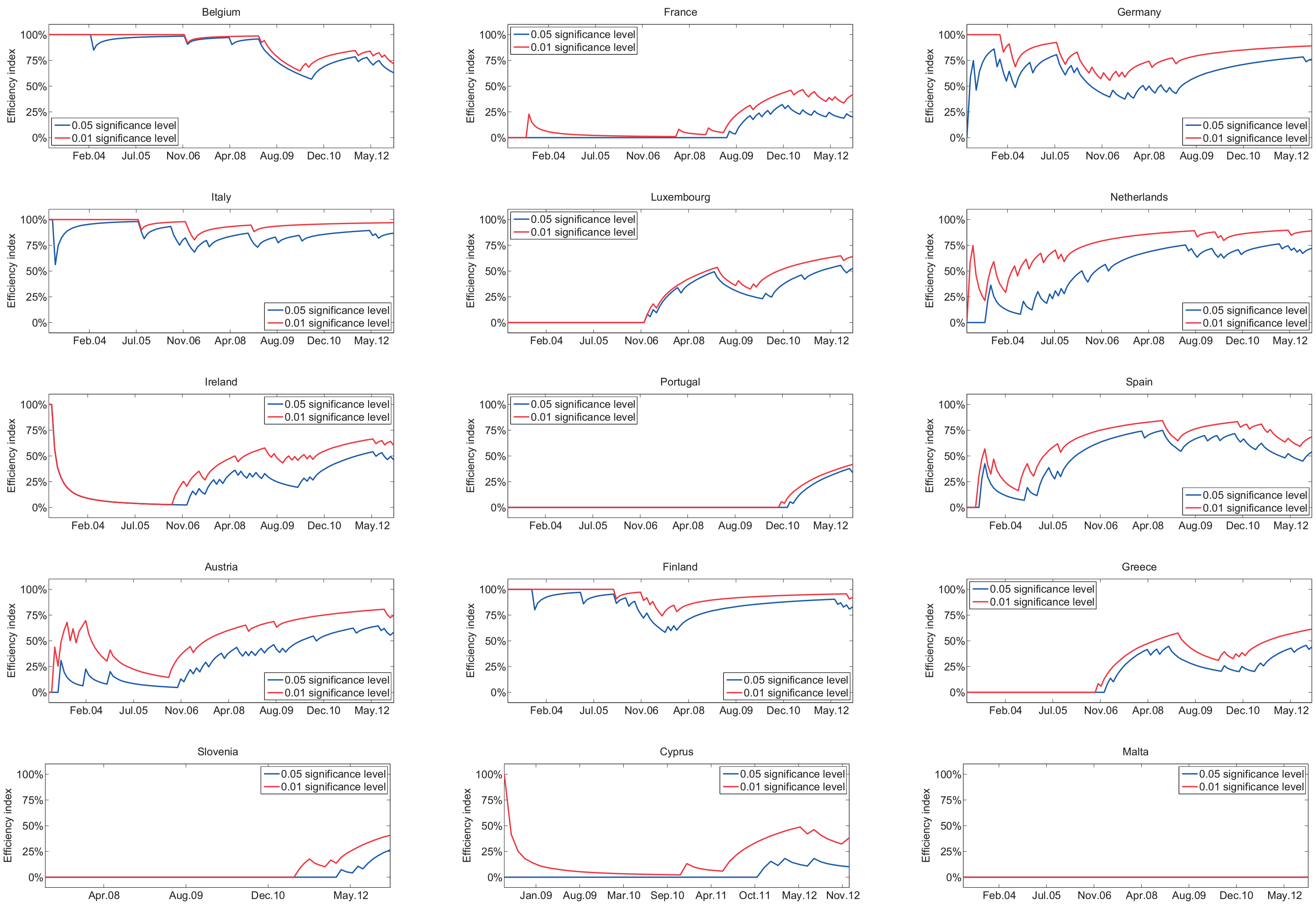

Figure 3: continued on next page

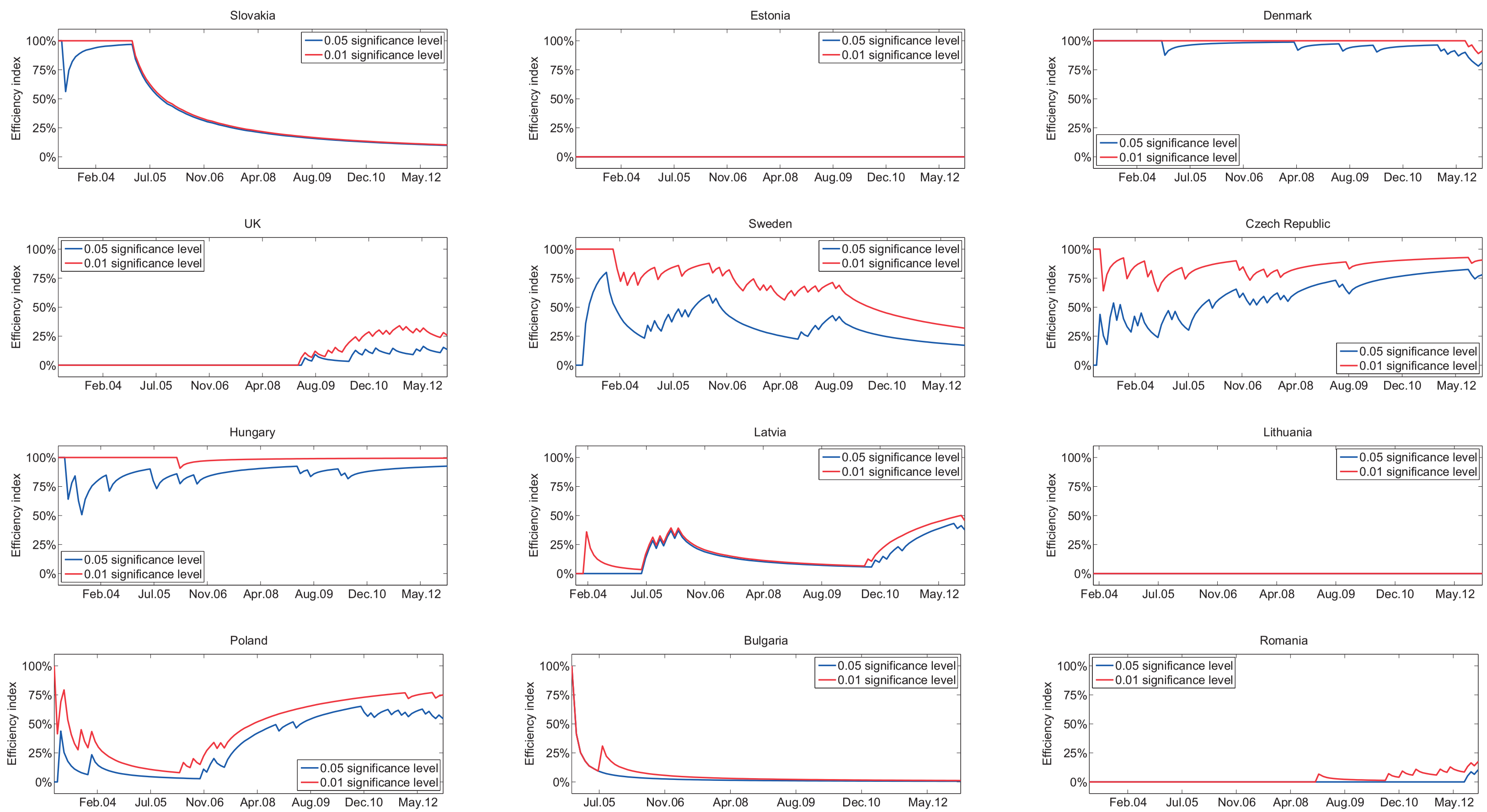

Figure 3: Efficiency index for each stock market in the European Union

France, Spain and Greece. Moreover, in general, market maturity is inversely related to the recovery time (in terms of efficiency) from the crisis. We could not obtain a strict conclusion on the effects of the usage of Euro on stock market efficiency. Similarly, we have mixed results on the effects of joining EU: while stock markets of Czech Republic and Poland converge to efficiency in a short time with a permanent characteristic, this effect has been temporary or not observed in other late members of EU.

After checking the robustness of our results, we finally introduce a time-varying stock market efficiency index that uses aggregate data and able to capture the dynamics of efficiency at any given time. We believe the index can provide guidance for policymakers, investors and portfolio managers.

Further research could explore the difference in stock market microstructure within these countries. These differences may explain how these markets react to external shocks and how they are absorbed by domestic prices. Taking into account liquidity, market depth, the role of institutional investors may provide additional useful information on the dynamics of stock markets and it seems an important step to be taken in the research agenda.

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A

Table 1: Analyzed stock markets

Country	Stock market index*	European Union	Eurozone	Time of study
Belgium	BEL 20	1952	1999	1999-2013
France	CAC 40	1952	1999	1999-2013
Germany	DAX	1952	1999	1999-2013
Italy	FTSEMIB	1952	1999	1999-2013
Luxembourg	LUXXX	1952	1999	1999-2013
Netherlands	AEX	1952	1999	1999-2013
Ireland	ISEQ	1973	1999	1999-2013
Portugal	PSI 20	1973	1999	1999-2013
Spain	IBEX 35	1986	1999	1999-2013
Austria	ATX	1995	1999	1999-2013
Finland	OMX Helsinki	1995	1999	1999-2013
Greece	ASE	1981	2001	1999-2013
Slovenia	SBITOP	2004	2007	2003-2013
Cyprus	CYSMMAPA	2004	2008	2004-2013
Malta	MALTEX	2004	2008	1999-2013
Slovakia	SKSM	2004	2009	1999-2013
Estonia	TALSE	2004	2011	1999-2013
Denmark	OMX Kopenhagen	1973	not member	1999-2013
UK	FTSE 100	1973	not member	1999-2013
Sweden	OMX Stockholm	1995	not member	1999-2013
Czech Republic	PX	2004	not member	1999-2013
Hungary	BUX	2004	not member	1999-2013
Latvia	OMX Riga	2004	not member	2000-2013
Lithuania	OMX Vilnius	2004	not member	2000-2013
Poland	WIG 20	2004	not member	1999-2013
Bulgaria	SOFIX	2007	not member	2000-2013
Romania	BET	2007	not member	1999-2013

*Data obtained from Bloomberg.

Table 2: Descriptive statistics of the time-varying $H(1)$ obtained from a rolling window of 4 year length

Market	Median	Mean	Max	Min	Std	Skewness	Kurtosis	J-B p-value	S-W p-value
Belgium	0.503	0.505	0.560	0.442	0.024	0.09	2.96	0.500	0.224
France	0.450	0.450	0.489	0.396	0.022	-0.15	2.39	0.244	0.396
Germany	0.478	0.482	0.524	0.437	0.018	0.02	2.73	0.500	0.388
Italy	0.497	0.495	0.533	0.457	0.017	-0.14	2.51	0.396	0.998
Luxembourg	0.538	0.554	0.652	0.455	0.053	0.38	1.77	0.016	0.000
Netherlands	0.491	0.490	0.543	0.440	0.024	0.06	2.11	0.091	0.112
Ireland	0.532	0.533	0.586	0.454	0.030	-0.28	2.77	0.326	0.120
Portugal	0.569	0.559	0.594	0.476	0.031	-1.24	3.43	0.001	0.000
Spain	0.475	0.475	0.520	0.437	0.017	0.25	2.73	0.396	0.873
Austria	0.526	0.522	0.562	0.452	0.024	-0.50	2.81	0.062	0.034
Finland	0.505	0.506	0.549	0.467	0.018	0.14	2.47	0.344	0.923
Greece	0.545	0.545	0.607	0.496	0.028	0.12	1.94	0.048	0.008
Slovenia	0.582	0.574	0.636	0.521	0.027	-0.34	2.33	0.171	0.019
Cyprus	0.556	0.561	0.609	0.529	0.023	0.59	2.22	0.065	0.006
Malta	0.649	0.652	0.715	0.602	0.027	0.53	2.55	0.039	0.003
Slovakia	0.609	0.594	0.656	0.504	0.044	-0.76	2.26	0.009	0.000
Estonia	0.634	0.642	0.711	0.572	0.036	0.28	1.96	0.034	0.001
Denmark	0.497	0.497	0.533	0.455	0.016	-0.16	2.48	0.334	0.750
UK	0.446	0.444	0.488	0.402	0.021	-0.10	2.10	0.085	0.090
Sweden	0.463	0.459	0.512	0.406	0.022	-0.46	2.78	0.076	0.014
Czech Republic	0.513	0.513	0.549	0.463	0.019	-0.31	2.34	0.090	0.067
Hungary	0.511	0.509	0.538	0.474	0.015	-0.41	2.55	0.084	0.092
Latvia	0.552	0.545	0.604	0.455	0.029	-0.55	2.86	0.050	0.019
Lithuania	0.658	0.657	0.689	0.616	0.013	-0.46	4.09	0.021	0.070
Poland	0.516	0.515	0.569	0.454	0.030	-0.10	1.79	0.030	0.001
Bulgaria	0.647	0.638	0.697	0.529	0.041	-0.82	2.71	0.014	0.000
Romania	0.566	0.566	0.612	0.514	0.022	-0.01	2.26	0.193	0.416

J-B and S-W denote Jarque-Bera and Shapiro-Wilk normality tests respectively.

Table 3: Efficiency ranking of stock markets based on analysis with a rolling window of 2 year length

Market	Sig. windows (5%)	Sig. windows (1%)	Total windows	Eff. ratio (5%)	Eff. ratio (1%)
Hungary	41	22	138	70.3%	84.1%
Finland	45	30	138	67.4%	78.3%
Denmark	48	24	138	65.2%	82.6%
Italy	56	41	140	60.0%	70.7%
Germany	59	44	140	57.9%	68.6%
Netherlands	60	41	141	57.5%	70.9%
Belgium	61	45	141	56.7%	68.1%
Czech Republic	61	44	138	55.8%	68.1%
Spain	70	50	139	49.6%	64.0%
Poland	79	57	138	42.8%	58.7%
Greece	79	69	137	42.3%	49.6%
Austria	79	57	136	41.9%	58.1%
Ireland	87	72	139	37.4%	48.2%
Slovakia	88	76	132	33.3%	42.4%
Luxembourg	94	76	138	31.9%	44.9%
Cyprus	52	40	73	28.8%	45.2%
Latvia	93	81	128	27.3%	36.7%
Sweden	103	91	138	25.4%	34.1%
Romania	101	93	135	25.2%	31.1%
Slovenia	68	65	89	23.6%	27.0%
Portugal	115	102	140	17.9%	27.1%
UK	115	107	139	17.3%	23.0%
France	126	117	141	10.6%	17.0%
Bulgaria	107	101	116	7.8%	12.9%
Estonia	132	132	139	5.0%	5.0%
Malta	135	133	136	0.7%	2.2%
Lithuania	125	125	125	0.0%	0.0%

1. A significant window (α%) is a window where market efficiency is rejected at α% significance level.
2. Efficiency ratio is calculated by dividing the number of insignificant windows by total number of windows.
3. Ordering from top to down is in descending order of efficiency based on efficiency ratio (5%).

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