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Time varying integration of European stock markets and monetary drivers

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This study analyzes time-varying integration of stock markets among fourteen European countries and its monetary drivers relevant to the two contrasting events — the introduction of Euro in 1999 and banking crisis of GIIPS in 2011. Our panel analysis reports evidence that monetary performance convergence, lower differentials in interest rates and inflation among EU countries, has been a key driver for the increase in integration of EU stock markets post EMU. Our qualitative analysis indicates that post EMU, the GDP differences among the EU countries have reverse relations with monetary performance convergence. This finding is in line with those of our quantitative study with a price-based indicator for integration.

1. Introduction

In recent decades, most of European financial markets have experienced two major but contrasting events; the introduction of the Euro and the banking crisis of GIIPS (i.e., Greece, Italy, Ireland, Portugal, and Spain). The use of Euro gave a tremendous fillip to stock market integration in Europe. A monetary institutional change such as EMU (European monetary union) has contributed positively to the integration process of European stock markets through a variety of channels. Similar inflation and interest rates faced by the EMU member states under a single monetary policy are expected to translate into a greater similarity of discount rates to value future cash flows and hence, a higher degree of stock market convergence in Europe. Furthermore, the reduced exchange risk from the introduction of the Euro lowers capital costs within EMU countries, leading to an efficient allocation of inter-regional capitals. Indeed, the Euro launch was *de facto* a major milestone in the integration process of currency and regulatory institutions. Meantime, the banking crisis of GIIPS in 2011 has rudely hampered the integration process of European stock markets. Recent literature has focused heavily on measuring the extent of European stock market integration driven by the EMU launch, although few studies address the latter shock effects on the market integration except the study of Bekaert et al. (2013).

To fill the lacuna in the literature, this study attempts to analyze systematically nature of time-varying integration of fourteen European stock markets and its monetary drivers relevant to the two contrasting events. We cover the longest sample periods of 1990–2014 to consider the economic impacts of the two critical events on the market integration. Using daily stock returns and the panel analysis using pairwise realized correlations of returns between fourteen European stock markets, this study controls unobserved heterogeneity in cross-sectional and time-series units to investigate dynamic interdependence of stock markets.

One strand of empirical studies on measuring a degree of integration of EU stock markets takes a structural approach within an international asset pricing model. (e.g., Hardouvelis et al., 2006; Brooks and DelNegro, 2004 among others). These studies analyze

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the integration of EU stock markets in the pre EMU period by considering European stock market returns and idiosyncratic risk factors of EU currencies at a time. The other strand of the empirical literature adapts a variety of the time series analysis techniques examining second-moments of time varying stock returns for the degree of EU stock market integration. A majority of such studies have relied on different time-series models, including models of GARCH, Markov switching, and co-integration models of stock returns with variances and covariances. (e.g., Morana and Beltratti, 2002; Capiello et al., 2006; Mylonidis and Kollias, 2010; Virk and Javed, 2017).[1] These time series analyses report that in the post EMU period, the spillover of return volatilities across European stock markets is mainly due to a stabilization of fundamentals and exchange volatilities for otherwise unstable European countries (e.g., Italy, Spain).

All the studies above depend on multi-stages methods by splitting the analysis into two or three stages to investigate the effects of the pre- and post-EMU on the integration of EU stock markets. One of problems with multi-stage methods may lead to biased estimation because errors from the first stage are omitted at the next stages, causing smaller errors than true ones. To overcome this problem, Beine and Candelon (2011) and Cipollini et al. (2015) adapt the panel analysis using pairwise realized correlations of returns to investigate dynamic interdependence of stock markets. Using pairwise correlations in a panel analysis allows us to effectively capture synchronization of stock markets across countries (Cipollini et al., 2015; Beine and Candelon, 2011; Dellas and Hess, 2005; Pretorius, 2002). In particular, Beine and Candelon (2011) look at the effects of trade and financial liberalization on comovement of emerging stock markets, whereas Cipollini et al. (2015) explore the effects of fiscal performances on synchronization (integration) across sovereign debt markets in Europe, emphasizing the post EMU periods. In a main context, our study focuses on the impacts of monetary performance convergences among EU countries on integration of fourteen European stock markets for the post EMU periods.

Our econometric strategy is similar to the approach of Cipollini et al. (2015) and Beine and Candelon (2011) with no loss of efficiency. Specifically, we use the realized moments method of Andersen et al. (2003) to measure the integration of EU stock returns for reliable inference on true underlying latent volatility in stock returns. For its drives, we adapts panel data techniques with pairwise realized correlations of EU stock returns to control unobserved heterogeneity cross-sectional as well as time-series units. Using the GARCH and stochastic (implied) volatility models, researchers may suffer from unconfident inference on the true underlying latent volatility in sample data. To overcome this problem, the *ex post* realized variances and correlations, the sum of the squares and cross-products of high frequency (e.g., daily or intraday) returns, should be a good alternative. Then volatility and correlation estimates are free from a measurement error as the sampling frequency of returns approaches infinity (Andersen et al., 2001a).

For explaining dynamic integration of European stock markets, this paper mainly focuses on analyzing the roles of monetary performance convergence between sample (pairwise) countries. To this end, this study uses interest rate and inflation differentials as proxies for monetary performance convergence among countries. This enables us to examine the direct impacts of the monetary convergence among sample countries for integration of European stock markets. Existing studies exclusively use a single monetary performance variable in each country (Baele, 2005; Fratzscher, 2002; Bekaert et al., 2013) or monetary convergence variables *vis-à-vis* German or Euro area weighted averaged monetary performance (Kim et al., 2005). In particular, Fratzscher (2002) and Kim et al. (2005) report that the correlation of inflations as a proxy for monetary performance convergence among EU countries was an important factor behind higher degree of comovement between these stock market returns while the correlation between interest rates was insignificant except for Italy only.[2]

We use comovement of European stock market returns as a proxy for time varying degree of integration among EU stock markets, based on an international capital flow model developed by Kim (2011) and Kim et al. (2015). The two studies of Kim (2011) and Kim et al. (2015) show evidence that the two variables (i.e., integration and comovement) of returns move together in EU countries having similarity of macroeconomic structure and depth and risk of stock market.[3] The higher degree of integration of stock markets between EU countries, the more likely their stock market returns would move together in the same direction, the enlarger risk sharing, and thus, less market risk. To explore this issue further, we additionally examine dynamic nature and drivers of integration of EU stock markets by using a qualitative approach.

Our empirical results from static and dynamic panel models indicate that the convergence in differentials of interest rate and inflation among the sample EU countries are significantly associated with an increase in the pairwise realized correlations of stock returns after the EMU launch. The findings also suggest that higher monetary similarities for pairs of EU countries have been a key driver for the increase in degree of integration of EU stock markets in the post EMU periods. In a qualitative perspective, our dynamic panel analyses do not indicate a direct effect of EMU on GDP convergence among EU countries, but higher differential of monetary performance are associated with lower GDP difference among EU countries.

The structure of this paper is as follows. Section 2 explains an analytical background and empirical methodologies for this study. Section 3 describes data used. Section 4 discusses empirical results. Section 5 briefly concludes.

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[1] Capiello et al. (2006) used an asymmetric Dynamic Conditional Correlation (DCC)-GARCH model, while Mylonidis and Kollias (2010) and Virk and Javed (2017) did use the different time-series techniques such as DCC-Mixed Data Sampling (MIDAS) and co-integration. Mylonidis and Kollias (2010) and Virk and Javed (2017) analyze dynamic converging patterns of European stock markets in the post EMU period, indicating the smaller markets show stronger integration than larger ones. In contrast, Baele (2005) and Berben and Jansen (2005), using the regime-switching GARCH model, shows that integration of European stock markets mainly took place during the pre EMU period of the 1980s — the first half of the 1990s.

[2] Note that inflation differentials might not be a good proxy for monetary performance convergence, as globalization led to an increase in global comovement of inflation over time. Inflation differentials could attribute to global shocks rather than domestic ones in explaining their dynamics. (e.g., Borio and Filardo, 2007; Kamber and Wong, 2018).

[3] Lee and Cho (2017), for instance, argue that common risk factors (e.g., oil price fluctuation) influence the covariance between stock returns of two countries with similar structure of oil-driven industries.

2. Analytical background and empirical methodology

2.1. Analytical background

This study relies on the factor model proposed by Ross (1976) for an analytical background for explaining the relationship between monetary performance similarities and European stock return correlations for pairs of countries. The factor models of Ross (1978) applied for this study are

$$R_A = \alpha_A + \sum_{i=1}^{K} \beta_{Ai} F_i + \varepsilon_A \tag{1}$$

$$\text{and } R_B = \alpha_B + \sum_{i=1}^{K} \beta_{Bi} F_i + \varepsilon_B \tag{2}$$

where K is factors $F_1, F_2, \ldots, F_K$ explaining country A's stock returns and country B's one, $R_B \forall i \neq j, Cov\left(F_i, F_j\right) = 0$, $\forall i, Cov\left(F_i, \varepsilon_A\right) = 0$, $\forall i, Cov\left(F_i, \varepsilon_B\right) = 0$, and $Cov\left(\varepsilon_A, \varepsilon_B\right) = 0$. Then We may make the covariance equation like below

$$Cov\left(R_A, R_B\right) = \sum_{i=1}^{K} \beta_{Ai}\beta_{Bi} Var\left(F_i\right) \tag{3}$$

$$\text{or } \rho_{A,B} = \sum_{i=1}^{K} \beta_{Ai}\beta_{Bi} \frac{\sigma_i^2}{\sigma_A \sigma_B} \tag{4}$$

where, $\sigma_i^2 = Var\left(F_i\right)$,$\sigma_A = \sqrt{Var\left(R_A\right)}$,$\sigma_B = \sqrt{Var\left(R_B\right)}$,$\rho_{A,B} = \frac{Cov(R_A,R_B)}{\sigma_A\sigma_B}$.

Then, one has

$$\forall k \in \mathrm{N}_K, \frac{\partial \rho_{A,B}}{\partial \sigma_k} = \beta_{Ak}\beta_{Bk} \frac{2\sigma_k}{\sigma_A \sigma_B} = \begin{cases} > 0, & if \quad \beta_{Ak}\beta_{Bk} > 0; \\ < 0, & if \quad \beta_{Ak}\beta_{Bk} < 0. \end{cases} \tag{5}$$

Note that the same change of a common risk factor may either increase or decrease the stock return covariance of two countries depending on the directions (same or opposite) of its effect on the stock returns of the two countries. Extending the above discussion based on the factor model for stock returns, we specify the regression model such as Eqs. (6)–(7) with other factors affecting only correlations of two different stock returns not affecting individual stock returns:

$$Cov\left(R_A, R_B\right) = \alpha_{AB} + \sum_{i=1}^{K} \beta_{Ai}\beta_{Bi} Var\left(F_i\right) + \sum_{j=1}^{L} \beta_j G_j + \varepsilon_{AB} \tag{6}$$

$$\text{or } \rho_{A,B} = \frac{\alpha_{AB}}{\sigma_A\sigma_B} + \sum_{i=1}^{K} \beta_{Ai}\beta_{Bi} \frac{\sigma_i^2}{\sigma_A\sigma_B} + \sum_{j=1}^{L} \beta_j \frac{G_j}{\sigma_A\sigma_B} + \frac{\varepsilon_{AB}}{\sigma_A\sigma_B} \tag{7}$$

where, $\sigma_i^2 = Var\left(F_i\right)$, $\sigma_A = \sqrt{Var\left(R_A\right)}$, $\sigma_B = \sqrt{Var\left(R_B\right)}$, $\rho_{A,B} = \frac{Cov(R_A,R_B)}{\sigma_A\sigma_B}$.

G_j denotes the additional other factors affecting only the correlation between two stock returns. Those common risk factors are unknown in general, and its data of high frequency are not available, causing difficulty with measuring the future uncertainty (σ_i). Instead, the higher frequency data (e.g., daily or weekly data) is recommended to compute the annual σ_is for the risk factors given one year of 52 weeks. This allows us to conduct a statistical estimation with minimum 30 observations.

2.2. Empirical methodology

2.2.1. Measuring dynamic integration of European stock markets

The *ex post* realized variances and correlations proxied for integration of EU stock markets in this study are measured by summing the squares and cross-products of high frequency (daily) returns. Then volatility and correlation estimates are free from a measurement error as the sampling frequency of the returns approaches infinity (Andersen et al., 2001a). The realized correlation measure is based on availability of higher frequency data. We use daily stock returns defined as $r_{i,t,d} = \ln(p_{i,t,d}/p_{i,t,d-1}) \times 100$ where p are stock indices. Note that the daily stock returns in this study do not include dividends. The measure of realized variance is given by

$$\sigma_{t,i}^2 = \sum_{d=1}^{D_t} [r_{i,t,d}]^2 \tag{8}$$

where $p_{i,t,d}$ are values of the stock index of country i at $t (t = 1, \ldots, 25)$ and day $d (d = 1, \ldots, D_t)$. D_t is the whole business day in the year t and the whole number of years is 25 in the full sample periods. Under the assumption of $E(r_{i,t,d} r_{i,t,d-1}) = 0$ and the stock market efficiency, this study measures realized covariance between the annual stock returns of country i and country j as

$$\sigma_{ij,t} = \sum_{d=1}^{D_t} [r_{i,t,d} \times r_{j,t,d}] \tag{9}$$

Finally, the realized correlation $\rho_{ij,t}$ measure is obtained as:

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sqrt{\sigma^2_{i,t} \times \sigma^2_{j,t}}} \tag{10}$$

Following Beine and Candelon (2011) and Cipollini et al. (2015), we also use a Fisher-Z transformation of $\rho_{ij,t}$ to make our panel regressions free from bounds on the predicted realized correlations:

$$\overline{\rho_{ij,t}} = \ln(\frac{1+\rho_{ij,t}}{1-\rho_{ij,t}}) \tag{11}$$

This paper estimates 91 unique pairwise realized correlations between 14 countries for each year. Given 25 annual observations, our dataset consists of 2275 observations for realized correlations.

2.2.2. Panel estimation

To examine determinants of European stock market integration, this paper relies on the use of panel data techniques to control for unobserved heterogeneity across cross sectional units. The panel model specified in this study is

$$\begin{aligned}\overline{\rho_{ij,t}} = {} & \alpha + \delta_{ij} + \beta_1 D_{EMU} + \beta_2 D_{GIIPS} + \beta_3 D_{Subprime} + \beta_4 X_{ij,t} + \beta_5 X_{ij,t} D_{EMU} + \beta_6 X_{ij,t} D_{GIIPS} \\ & + \beta_7 X_{ij,t} D_{Subprime} + \beta_8 C + \varepsilon_{ij,t} \end{aligned} \tag{12}$$

$$(i \times j) \in [1, \dots, N(14)], \qquad t = 1, \dots, T(25)$$

where the dependent variable $\overline{\rho_{ij,t}}$ is realized correlations (hereafter, correlation) over time, α is a constant, δ_{ij} represents (time-invariant and unobserved) cross-section effects, which can be fixed or random, and $\varepsilon_{ij,t}$ is the error term over time. D_{EMU} represents an EMU intercept dummy with values 0 up to 1998 and 1 from 1999 onwards. D_{GIIPS} denotes an intercept dummy of the GIIPS banking crisis that takes values 1 over years 2010–2011 and 0 otherwise. $D_{Subprime}$ is an intercept dummy of the US Subprime crisis values 1 over 2007–2008 and 0 otherwise. $X_{ij,t}$ is a vector of two explanatory variables of the inflation differentials and (short term) interest rate differentials as proxies for monetary performance convergence among sample countries. D is a vector of interactive slope dummies that includes D_{EMU}, D_{GIIPS}, and $D_{Subpime}$ on the two explanatory variables, respectively. C is a vector of control variables.

In this paper, the time series dimension T is equal to 25 (annual observations) and the cross-section dimension N is given by $(\frac{14 \times 13}{2})$, which equals 91, that is, the number of unique annual pairwise realized correlations among fourteen EU stock markets. The annual realized correlations considerably relieve a microstructure noise, which is more likely to arise at higher frequency (e.g., in presence of intra-data). Given that daily stock indices are used to obtain annual realized correlations, this study argues that the 260 observations employed each year allow us to obtain a good proxy of the true correlation (at one year horizon).

For regression estimations, this study runs the fixed effects (FE), random effects (RE) models and the pooled OLS model, respectively. We use the OLS method for the fixed effects model and the generalized least squares (GLS) method for the Random effects model, respectively. To assess which panel model is statistically appropriate, this study employs the Breusch–Pagan Lagrange Multiplier (*LM*) and Hausman tests. For a diagnostic test, we account for the problem of the *CSD* between error terms in panel datasets. For robustness, we check for endogeneity bias by using an instrumental variable (IV) estimation for the benchmark results in the study. This study also explores an effect of a persistence of the dependent variable by running dynamic panel regressions.

3. Data issues

3.1. Stock return data

We use daily stock returns for high frequency data from fourteen European countries during 1st January 1990–29th December 2014. These data include the eleven Euro-zone countries (i.e., Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain) and three non Euro-zone but major EU countries (i.e., Denmark, Sweden, and the UK).[4] All the national stock market indices used in this paper are available from the Datastream International, and given in a US dollar unit. The national stock market returns in the study are computed as the log differences in the closing index levels from one trading day to the next day such that $r_{i,t,d} = \ln(p_{i,t,d}/p_{i,t,d-1}) \times 100$ for the stock market i at year $t(t = 1, \dots, 25)$ and day $d(d = 1, \dots, D_t)$ where D_t is the total number of business days (260) in individual year t.

3.2. Exogenous explanatory variables

Extant studies propose monetary factors such as inflation and interest rate to explain international stock market linkages (e.g., Fratzscher, 2002; Baele, 2005; Beine and Candelon, 2011; Morana and Beltratti, 2002; Kim et al., 2005). Moreover, the EMU implements a single monetary policy to result in monetary convergence of interest rate and inflation among EMU countries.[5] This

[4] This study excludes seven new Euro-zone countries of Cyprus, Estonia, Latvia, Lithuania, Malta, Slovakia, Slovenia where joined the EMU later. Luxembourg, one of initial EMU member states, is also excluded due to unavailability of data of stock return and interest rate for the full sample periods.

[5] As aforementioned, inflation (differentials) might not be a good proxy for monetary performance when globalization contributes to time-varying comovement among inflations in countries (See (Borio and Filardo, 2007; Kamber and Wong, 2018) for its details).

paper employs annual interest rate and inflation differentials of pairs of sample EU countries to proxy EMU convergence. Since this study focuses on low frequency financial integration it uses annual realized correlations for the dependent variable and annual observations for each explanatory variable as well.

a. Inflation differentials

Inflation differentials between pairs of the sample countries are computed as differences in logarithm of consumer price indices (CPI) of each country. Note that this paper uses absolute value for this variable rather than the actual difference because our concern is not about which country's inflation rate is higher, but about how large the differential is (Pretorius, 2002; Beine and Candelon, 2011). The CPI for each country is composed of annual observations from the OECD-MEI (OECD-Main Economic Indicators) database for the entire periods.This study expects the negative sign for the slope coefficient for this variable. The lower differentials between pairs of countries would proxy higher degree of monetary policy convergence and then, this would affect positively on EU stock market integration.

b. Interest rate differentials

Short-term interest rate differentials are differences in the three-month interest rates of pairs of all the sample countries at the annual frequency. Along the same vein with the inflation differentials, this paper uses absolute value for the inflation differentials. The interest rates data are also available from the OECD-MEI database. Note that for periods 1990–1994, the interest rates of Greece are not available from the same source and so, we replace ones from Datastream International for the missing values. We expect the negative sign for the slope coefficient of the interest rate differentials. This means that lower differentials between pairs of countries have a positive effect on the integration.

3.2.1. Dummy variables

a. Two dummies relevant to EMU

The panel models in this study allow two EMU dummies to be considered. The first is a time dummy related to the introduction of Euro in Europe, capturing an intercept shift. The second is a EMU slope dummies interacting with the respective differentials of inflation and interest rates between pairs of sample EU countries. Both have values of 1 from 1st January 1999 and 0 otherwise. In particular, we use the EMU intercept dummy to capture the direct impact of EMU (the elimination of exchange risk) on integration of European stock markets. The EMU slope dummies, interactive with the two main explanatory variables, are also used to analyze the possible impacts of monetary policy convergence on the market integration post EMU. We expect that the EMU intercept dummy has a positive sign for its slope coefficient while the two EMU slope dummies have a negative one for their slope coefficients (-).

b. Two dummies relevant to GIIPS banking crisis

To examine the effect of the GIIPS banking crisis in 2010–2011 on integration of EU stock markets, this paper includes the time dummy of capturing an intercept shift of the GIIPS banking crisis in the panel models. We expect a negative sign for the slope coefficient of this dummy that suggests a decoupling effect in unstable times. Like the EMU slope dummies, we use the GIIPS slope dummies interactive with the two explanatory variables to examine the effects of monetary policy convergence on the integration at the GIIPS crisis. Both take values 1 over the years 2010–2012 and 0 otherwise.

c. Two dummies relevant to US subprime crisis

This study includes another time dummy of capturing an intercept shift to find the effect of the US subprime crisis in 2007–2008 in our panel estimations. This takes values 1 over 2007–2008 and 0 otherwise. We add the US subprime slope dummies interacting with the two explanatory variables whose take values 1 over the two years 2007–2008 and 0 otherwise as well.

3.2.2. Control variables

This paper uses a variety of control variables to examine the effects of the monetary performance convergence across the sample countries on integration of stock markets in Europe. The variable *IPDif* denoted for industrial production differentials is used to control for absolute value of difference of industrial production index among sample countries. The industrial production indices of the sample countries are from the OECD-MEI database. To control for the possible effects of difference of stock market development among countries, we use difference of stock market capitalization to GDP (*MarkCapDif*) between countries in our panel models.[6] An availability of raw data of stock market capitalizations for individual countries is limited to periods 1990–2012 from the World Development Indicator (WDI). Raw data for Ireland is available only for the periods 1996–2012 from the database source. The variable *VDAX* (the implied volatility of DAX equity index option) is used to examine the effect of market participants' expectation for a future stock market uncertainty on the stock market integration. To control for the effect of a rate of global risk-free return, this paper uses a logarithm of a three months short term US-treasury bill denoted in *lnUS-Tbill*. The frequency of these exogenous variables is a yearly frequency to match with other variables. Raw data for *VDAX* and 3-months *lnUS-Tbill* are available from the Datastream International and those for the industrial production of sample countries are available from the OECD-MEI database.

Table 1 reports the descriptive statistics of the exogenous variables with the panel data structure for this study. We need to concentrate on the median rather the mean for the two main explanatory variables because they show a skewed distribution. In

[6] We should address that this study does not distinguish between demand and supply shocks for market capitalization (i.e., stock market development) differentials and industrial production (i.e., economic activity of output) differentials of the sample countries. Campos and Macchiarelli (2016, 2018) rely the methodology of Bayoumi and Eichengreen (1997) who decompose permanent and temporary shocks for macroeconomic variables. Campos and Macchiarelli (2016, 2018) consider the shocks to output whereas Beaudry and Portier (2006) do the dynamics of stock returns.

Table 1
Descriptive statistics for exogenous independent variables.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Min	Median	Max	Obs.
InterestRateDifferentials (InterDif)	1.3581	2.3511	2.4385	9.0652	0	0.3	13.1	N = 2275 n=91 T = 25
InflationDifferentials (InfDif)	0.0160	0.0217	3.434198	17.4261	0	0.0093	0.1641	N = 2275 n=91 T = 25
IndustrialProductionDifferentials (IPDif)	0.1624	0.1575	1.2225	4.5127	0	0.1	0.8	N = 2275 n=91 T = 25
MarketCapitalizatonDifferentials (MarkCapDif)	0.1981	0.2131	2.2944	9.3525	0.0005	0.1314	1.5406	N = 2016 N=91 T = 22.1538
VDAX	20.2176	11.7026	0.4756	3.6289	0	17.91	51.13	N = 2275 n=91 T = 25
lnUS3mTreasuryBill (lnUS-T*bill*)	−0.1900	0.9084	−1.8707	7.2517	−3.3982	−0.0703	0.9163	N = 2275 n=91 T = 25

Notes. N, n and T denote the numbers of total observations, panel groups and years, respectively. Raw data of country specific-stock market capitalizations are available for the periods 1990–2012 except for Ireland having those over periods 1995–2012.

Table 1, the median of the (short) interest rate differentials is some 0.3 over the full sample periods and the corresponding figure of inflation differentials is around 0.009. These figures may ensconce some variation over time. The kurtosis of both variables also shows high figures that present a feature of the leptokurtic distribution gathering heavily toward the center. The skewness and kurtosis for the whole control variable also present non-normality.

Prior to the actual panel analysis, the statistics of the IPS (Im et al., 2003) and Fisher type (Choi, 2001) tests reject the null of the panel unit root in the levels of all the panel data variables at the standard levels. The ADF and PP statistics for stationarities for the two single series of the VDAX and the US 3 month interest rate significantly reject the null of unit root in the level of the former and in the difference of the latter. In addition, most correlation values across all the independent variables show low estimates except for a relatively high value (0.664) between interest rate and inflation differentials.[7]

4. Empirical results

4.1. Baseline results of panel regressions

This subsection analyzes the main results of the panel data regressions with fixed effects or with random effects. Table 2 shows the static panel regression results for drivers of European stock market integration over the full sample periods 1990–2014.

The *LM* (Lagrange Multiplier) test proposed by Breusch and Pagan (1980) is used for comparing the simple pooled OLS and RE models. All the *LM* statistics (2831.71, 2838.06 and 1864.36) for the whole Regression in Table 3 far exceed the 95 percent significance level for the $\chi^2_{(1)}$ distribution. The statistics suggest that the RE models for all the regression specifications are preferred to the pooled OLS regression models. To test for whether the coefficients by the efficient RE estimator equal the ones estimated by the consistent FE estimator, this paper employs the Hausman test. The Hausman statistics (13.89) in Regression 1 does reject the null at the 5% level and suggest a preference of the FE model. However, the statistics in Regressions 2 and 3 do not reject the null at the standard level and then suggest a preference of the RE model.

First of all, as for the EMU effect on integration (i.e., realized correlations) of European stock markets, all the panel regressions on Table 2 estimate highly significant and positive coefficients at 0.616, 0.683, 0.739, respectively, for the EMU intercept dummy (D_{EMU}). The result suggests that the exchange rate stability due to the Euro's introduction has significantly stimulated integration among stock markets in Europe. This is in line with the extant studies of Fratzscher (2002), Morana and Beltratti (2002), Kim et al. (2005) and Capiello et al. (2006) that address the EMU launch has contributed to an increase in convergence across EU stock markets. However, this result diverges from the empirical results of Berben and Jansen (2005) and Baele (2005) who suggest the event has a limited impact on the integration. Similarly, Bekaert et al. (2013) report evidence that the EU membership is an important driver for explaining integration of European financial markets rather than the Euro' introduction.

The banking crisis caused by the European GIIPS countries shows a significant positive effect on the market integration because the GIIPS banking crisis dummy (D_{GIIPS}) has highly significant positive coefficients on all the specifications. One possible explanation for this counterintuitive result would be due to a transient volatility spillover effect rather than a return spillover one among EU stock markets during the crisis periods. Along with a similar vein, the significantly positive estimates on the US Subprime

[7] The specific results for the unit root and correlation tests are omitted to consider space but available upon request.

Table 2
Benchmark results of the static panel regressions for European stock market integration.

Variables	Reg.1	Reg.2	Reg.3
Constant	1.064*** (0.025)	1.032*** (0.034)	1.377*** (0.045)
D_{EMU}	0.616*** (0.032)	0.683*** (0.034)	0.739*** (0.043)
D_{GIIPS}	1.034*** (0.031)	1.045*** (0.040)	1.215*** (0.052)
$D_{Subprime}$	0.647*** (0.041)	0.633*** (0.064)	0.382*** (0.192)
InterDif	−0.003 (0.006)		−0.024*** (0.008)
*InterDif*_D_{EMU}	−0.085*** (0.010)		−0.043*** (0.014)
*InterDif*_D_{GIIPS}	0.374*** (0.092)		0.115 (0.137)
*InterDif*_$D_{Subprime}$	0.279*** (0.053)		0.262*** (0.049)
InfDif		0.792** (0.507)	−1.006 (0.736)
*InfDif*_D_{EMU}		−7.495*** (2.159)	−5.333** (1.798)
*InfDif*_D_{GIIPS}		5.425** (2.603)	−8.020** (3.396)
*InfDif*_$D_{Subprime}$		19.680 (24.340)	40.879 (66.137)
IPDif			−0.112* (0.065)
MarkCapDif			−0.192*** (0.055)
VDAX			−0.015*** (0.001)
lnUS-Tbill			−0.257*** (0.013)
Num. of Obs.	2275	2275	2016
Number of groups	91	91	91
Correlation (δ_i, x_i)	0.016	0	0
R^2	0.413	0.396	0.520
$F - value$ or $Wald - \chi^2_{(k)}$	550.63*** <1%	6671.10*** <1%	3671.88*** <1%
LM $(\chi^2_{(1)})$ statistics	2831.71*** <1%	2838.06*** <1%	1864.36*** <1%
Hausman $(\chi^2_{(k)})$ statistics	13.89** <5%	9.24 > 10%	6.97 > 10%
Pesaran *CDS* statistics	170.126*** <1%	178.428*** <1%	138.162*** <1%

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses of each variable indicate robust standard errors. $F - value$ and $Wald - \chi^2_{(k)}$ are joint test values for the FE and RE models, respectively.

crisis dummy ($D_{Subprime}$) in Table 2 suggest that another global economic crisis caused by the US Subprime crisis in 2007–2008 made a contagion effect for interdependence among EU stock markets. The extent of the contagion effect is weaker than that of the GIIPS crisis.

Regarding the effects of monetary performance convergence between sample EU countries, Regression 1 estimates an insignificant coefficient for the interest rate differentials (*InterDif*). However, Regressions 1 and 3 estimate highly significant negative coefficients (−0.085, −0.043) for the EMU slope dummy (*InterDif*_D_{EMU}) interactive with this variable. The results address that pre EMU, interest rate differentials between sample EU countries had no influence on integration of EU stock markets but post EMU, the lower differentials have driven an increase of the market integration. Overall, these findings on the interest differentials go against Fratzscher (2002) who suggests that short term interest rates have been a driving force behind integration of EU stock markets pre EMU. Baele (2005) also suggest that interest rate (monetary) convergence intensified European shock spillover in the second half of

Table 3
Results of the panel regressions for omitted variable biases.

Variables	Reg.1	Reg.2	Reg.3	Reg.4
Constant	1.917*** (0.064)	1.432*** (0.058)	1.381*** (0.045)	1.393*** (0.051)
D_{EMU}	0.463*** (0.048)	0.723*** (0.046)	0.747*** (0.046)	0.740*** (0.046)
D_{GIIPS}	1.182*** (0.046)	1.225*** (0.051)	1.212*** (0.052)	1.217*** (0.052)
$D_{Subprime}$	0.321*** (0.142)	0.365** (0.183)	0.369*** (0.187)	0.385*** (0.192)
InterDif	−0.030** (0.015)	−0.020*** (0.008)	−0.016* (0.009)	−0.024*** (0.008)
*InterDif*_D_{EMU}	−0.013 (0.017)	−0.039*** (0.014)	−0.041*** (0.014)	−0.044*** (0.014)
*InterDif*_D_{GIIPS}	0.062 (0.128)	0.218 (0.133)	0.148 (0.137)	0.153 (0.137)
*InterDif*_$D_{Subprime}$	0.240*** (0.048)	0.269*** (0.050)	0.258*** (0.050)	0.264*** (0.050)
InfDif	2.794 (3.244)	−1.278* (0.733)	−1.141 (0.885)	−1.055 (0.738)
*InfDif*_D_{EMU}	−7.917** (3.438)	−5.261*** (1.787)	−6.186*** (1.848)	−5.380*** (1.806)
*InfDif*_D_{GIIPS}	−9.305** (3.064)	−7.734** (3.330)	−8.079** (3.408)	−8.093*** (3.426)
*InfDif*_$D_{Subprime}$	20.725 (49.304)	49.427 (62.939)	41.420 (64.186)	39.847 (66.017)
IPDif	0.053 (0.065)	−0.114* (0.065)	−0.114* (0.065)	−0.111* (0.065)
MarkCapDif	−0.196*** (0.067)	−0.191*** (0.055)	−0.180*** (0.056)	−0.198*** (0.056)
VDAX	−0.027*** (0.001)	−0.015*** (0.001)	−0.016*** (0.001)	−0.015*** (0.001)
lnUS-Tbill	−0.316*** (0.013)	−0.259*** (0.013)	−0.259*** (0.013)	−0.258*** (0.014)
lnFinStaDif	−0.001 (0.011)			
FinAcesDif		0.009 (0.116)		
FinDepDif		−0.422*** (0.101)		
FinEffiDif		0.502** (0.217)		
FinOpenDif			−0.066* (0.035)	
TraOpenDif				0.002 (0.004)
Num. of Obs.	1457	2016	2016	2016
Number of groups	91	91	91	91
Correlation (δ_i, x_i)	0	0	0	0
R^2	0.470	0.539	0.520	0.522
$F-value$ or $Wald-\chi^2_{(k)}$	2882.65*** <1%	3727.76*** <1%	3653.92*** <1%	3645.97*** <1%
LM $(\chi^2_{(1)})$ statistics	2151.80*** <1%	1607.79*** <1%	1857.01*** <1%	1708.57*** <1%
Hausman $(\chi^2_{(k)})$ statistics	−2.84 > 10%	21.87 > 10%	−1.85 > 10%	−70.30 > 10%
Pesaran *CDS* statistics	114.715*** <1%	136.614*** <1%	137.459*** <1%	137.990*** <1%

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses of each variable indicate robust standard errors. $F-value$ and $Wald-\chi^2_{(k)}$ are joint test values for the FE and RE models, respectively.

the 1980s and the first half of the 1990s before the EMU launch. For the post EMU periods, Morana and Beltratti (2002) and Kim et al. (2005) argue that the effect of short interest rates has been limited to just some country (e.g., Italy) unlike the finding from this study. Regression 3 shows an insignificant estimate for the GIIPS slope dummy (*InterDif*_D_{GIIPS}) interactive with this variable on realized correlations of EU stock market returns although Regression 1 of excluding any control variables shows a significant value. Regressions 1 and 3 for the Subprime slope dummy (*InterDif*_D_{GIIPS}) interacting with this variable estimate significant positive coefficients at 0.279 and 0.262, respectively, and suggest a positive effect on the market integration.

As for the effects of the other proxy (i.e., inflation differentials) for monetary performance convergence, the panel Regressions 2 and 3 with random effects estimate mixed coefficients of a significant negative coefficient and an insignificant one on the inflation differentials (*InfDif*). However, for the EMU slope dummy (*InfDif*_D_{EMU}) interactive with the inflation differentials, our panel Regressions 1 and 3 show significantly negative estimates (−7.495 and −5.333) at the 1% and 5% levels, respectively. The results suggest that post EMU, the inflation (monetary) performance similarity (i.e., the lower inflation differentials) among the sample countries had a positive influence on stock market integration in Europe.

In association with the findings, extant studies such as Baele (2005), Fratzscher (2002), Kim et al. (2005) and Bekaert et al. (2013) argue that price stability (CPI) is an important factor for EU stock market integration. Overall, these results obtainable from the empirical tests for the post EMU periods are in line with our theoretical expectation discussed in Section 2.1. For the inflation differentials interactive with the GIIPS crisis (*InfDif*_D_{GIIPS}), Regressions 2 and 3 estimate contrasting coefficients (5.425, −8.020) at 5% level, respectively. In association with this result, casting glance at Table 3 for checking omitted variable biases in advance would be useful. That is, for the *InfDif*_D_{GIIPS}, all the regressions in Table 3 estimate very significant negative values and then suggests a negative impact of the inflation differentials on the market integration during the GIIPS crisis. For the inflation differentials interacting with the Subprime crisis (*InfDif*_$D_{Subprime}$), the insignificant estimates from Regressions 2 and 3 of Table 2 suggests no effect of inflation differentials on the integration during the economic crisis.

The specific results of control variables in Table 2 are presented on Regression 3. Regression 3 estimate a significantly positive coefficient (−0.112) for the industrial production differentials (*IPDif*) on realized correlations of EU stock returns. This suggests a negative relation with economic growth differentials for pairs of sample countries on integration of EU stock markets. In Regression 3, we also observe a significantly negative coefficient (−0.192) for the stock market capitalization differentials (*MarkCapDif)*, a proxy for stock market similarity (i.e., economic structure similarity) among sample countries. This addresses that a higher economic similarity among sample countries is significantly associated with an increase in integration of stock markets in Europe. This finding goes with Kim (2011) and Kim et al. (2015) who suggest a validity of international portfolio flows that comovement and integration of capital markets across countries move toward the same direction, if economic structures across them are similar. The VDAX has a negative estimate (−0.015) at 1% level, suggesting that an investors' low expectation for future financial market uncertainty is associated with the stock market integration in this region. In general, market participants are inclined to increase their portfolio with stocks of risky asset (bonds of safe one) when an uncertainty for future economy is low (high). Lastly, Regression 3 makes a significantly negative coefficient (−0.257) for the rate of global risk-free return (*lnUS-Tbill*) proxied by the log difference of the 3 months US treasury bill. The result addresses that a lower rate of global risk free return contributes to an increase in integration of EU stock markets. This may imply that investors are likely to increase their portfolio with stock assets of risky ones in this region when the global risk free rate of return is low.

We substantially observe a cross sectional dependence (CSD) across error terms in panel datasets because all the Pesaran CSD statistics in Table 2 are highly significant at 1% level. To account for the CDS problem, this study conducts the panel data regressions with the Driscoll and Kraay standard errors (see Driscoll and Kraay, 1998 for its details). Our diagnostic tests using the panel regression with Driscoll and Kraay standard errors support our baseline results still.[8]

4.2. Omitted variable biases

Our panel models in Table 2 do not account for an observed cross-country heterogeneity although the models consider time-invariant and unobserved one across countries. This may cause the main regression results biased, due to a possibility of omitted variables in the models. To check for the omitted variable bias problem, we run the panel regressions by adding other time-varying control variables in the panel regression models.

For this test, our study adds each of the differentials of financial structures, financial openness and trade openness among sample countries to our benchmark panel regression models in Table 2. In particular, the market capitalization differentials among countries partly capture the extent of stock (financial) market differences among countries (Benbouzid et al., 2017). To control for other important dimensions of financial structure differences among countries, we add other financial structure differentials; the differentials of financial stability, financial depth, financial access, and financial efficiency, respectively. The financial stability differentials captured by the default distance differences are proxied by differences of the Bank Z-cores among sample EU countries. The raw data of this variable are collectable from the Global Financial Development Database (GFDD) of the World Bank. Note that the data of the Z-score cover only the periods 1996 to 2014, due to unavailability of the data for all the sample countries over the full sample periods. The financial depth differentials (*FinDepDif*) among countries are calculated by differences of compilation of bank credit to the private sector in percent of GDP, pension fund assets to GDP, mutual fund assets to GDP, and insurance premiums, life and non-life to GDP. The financial access differentials (*FinAcesDif*) are measured by differences of compilation of bank branches and ATMs per 100,100 adults among countries. The financial efficiency differentials (*FinEffiDif*) are differences of compilation of

[8] The specific estimates are omitted to save space but available upon any request.

banking sector net interest margin, lending-deposits spread, non-interest income to total income, overhead costs to total assets, return on assets, and return on equity. The raw data of the three variables are collectable from the IMF-Financial Development Index Database over the entire periods 1990–2014.

The financial openness differentials (*FinOpenDif*) to account for the effect of the differences of financial openness degree among countries are proxied by differences of the Chinn-Ito index (KAOPEN). This index devised by Chinn and Ito (2006) is commonly used in international economics and finance. The raw data of this index are collectable from the website-http://web.pdx.edu/~ito/Chinn-Ito_website.htm. The trade openness differentials (*TraOpenDif*) to consider the effect of the trade openness degree for pairs of countries are measured by differences of sum of exports and imports as percentage of GDP for each pair.[9] The raw data of this variable are gatherable from the world development indicator (WDI) of the World Bank.

For a matter of clarity and comparison, we estimate the four types of the regression models by adding these omitted variables one after another to the set of controls. In each regression, the financial stability differentials (*FinstaDif*) variable is in log difference but the other omitted variables are in level as the panel unitroot statistics strongly reject the null of the unit root for the difference of the *FinstaDif* but for the level of the other omitted variables.[10] Table 3 shows the results of our panel regressions for testing for the omitted variable biases. Regressions 1, 2, 3, and 4 include the differentials of financial stability, financial structures, financial openness, and trade openness for pairs of sample countries, respectively to the set of controls. In a qualitative perspective, the most estimates from the new four types of the panel regressions are nearly identical to the estimates from our benchmark regressions in Table 2. The only exceptions are on insignificant estimates for both the EMU slope dummy ($InterDif\_D_{EMU}$) interactive with the interest rate differentials and the industrial production differentials (*IPDif*) in Regression 1 adding the financial stability differentials (*lnFinStaDif*) to the set of controls. The results suggest that our main results without the omitted variables are still robust to ones from the panel estimations with the omitted ones.

As for the effects of the omitted variables, Regression 2 estimates a negative coefficient (−0.422) for financial depth differentials but a (counterintuitive) positive one (0.502) for the financial efficiency differentials at the standard levels. The financial openness differentials variable in Regression 3 have a significant negative value (−0.066) which suggests a reverse relation on EU stock market integration as expected. Regression 4 estimate an insignificant coefficient for the trade openness differentials.

4.3. Endogeneity bias test using instrumental variables

This study attempts to check for endogeneity biases on the baseline estimates obtained from the panel regressions in Table 2 by using instrumental variable (IV) estimation. Instruments are proxied by the 1st lag of the two monetary convergence variables. According to Wooldridge (2008), lag variables are highly correlated with their original ones, and, thus, insulate explanatory variables from their error terms.

Table 4 presents results for the whole model with the instrumental variables. The results in Table 4 show that overall, the empirical findings for the full sample periods are qualitatively (perfectly) identical to the ones in Table 2 previously discussed which ignored an endogeneity biases. Hence, our baseline results in Table 2 are confirmed although this study considers a possibility of endogeneity biases in the whole panel regression. The Hausman statistic (164.02) support the panel model with fixed effects for Regression 1 as the best fit to the data because the statistic does strongly reject the null hypothesis at the 1% significance level. Meanwhile, the statistics for Regressions 2 and 3 do not reject the null at the standard level and then, support the panel model with random effects as the best fit.

In addition, we conduct the Granger causality test between the two monetary performance differentials variables and realized correlations (i.e., integration) among EU stock returns to check for an endogeneity problem between them. We find evidence that the monetary performance differences Granger causes stock market integration significantly but the reverse does not at all.[11]

4.4. Dynamic panel regressions

To examine an effect of a persistence of the dependent variable on integration of EU stock markets, this paper additionally specifies linear dynamic panel models with AR (2) of the dependent variable of the realized correlations in each panel model.

The results are presented in Table 5. Overall, the estimation results obtainable from the linear dynamic panel models are qualitatively similar with our baseline results obtainable from the static panel models for our main explanatory variables and for most exogenous control and dummy variables in Table 2. Only exceptions in Table 5 are on the interest rate differentials (*InterDif*) in Regressions 1 and 3, on the inflation differentials in Regression 2 and on the industrial production differentials *(IPDif)* in Regression 3, respectively. The significant (insignificant) interest rate differentials in Regression 3 (1) of Table 2 are changed into insignificant (significant) one in Regression 3 of Table 5 where shows the linear dynamic panel estimation results. The significant inflation differentials in Regression 2 of Table 2 are changed into an insignificant one in the regression of Table 5. The case for the industrial production differentials also shows a similar magnitude. Even if so, our main results for the post EMU periods still remain valid. That is, our dynamic panel regression results for the two main explanatory variables (i.e., monetary performance similarities) are economically similar with the baseline results from the static panel regressions in Table 2.

[9] To account for a trade effect, Baxter and Kouparitsas (2005) and Beine and Candelon (2011) use the degree of bilateral trade for pairs of countries and Flood and Rose (2010) use distance between countries, respectively. Due to a difficulty of obtaining the information over the full sample periods for the whole country, this study uses the trade openness differentials for pairs of countries.

[10] The specific results for the panel-unit root tests are omitted to save space but are ready to any request.

[11] The specific results for this test are not reported but available upon request.

Table 4
Results of the endogeneity bias tests with instrumental variables.

Variables	Reg.1	Reg.2	Reg.3
Constant	1.067*** (0.028)	1.022*** (0.039)	1.421*** (0.046)
D_{EMU}	0.614*** (0.032)	0.693*** (0.034)	0.750*** (0.040)
D_{GIIPS}	1.032*** (0.041)	1.042*** (0.046)	1.204*** (0.054)
$D_{Subprime}$	0.646*** (0.046)	0.620*** (0.301)	0.362*** (0.283)
InterDif	0.001 (0.007)		−0.028*** (0.009)
*InterDif*_D_{EMU}	−0.089*** (0.017)		−0.037** (0.018)
*InterDif*_D_{GIIPS}	0.376*** (0.118)		0.143 (0.148)
*InterDif*_$D_{Subprime}$	0.278*** (0.073)		0.261*** (0.070)
InfDif		1.940*** (0.731)	0.251 (1.004)
*InfDif*_D_{EMU}		−8.690*** (1.946)	−6.365*** (2.102)
*InfDif*_D_{GIIPS}		5.579** (2.632)	−8.044** (3.697)
*InfDif*_$D_{Subprime}$		21.552 (101.407)	37.206 (95.950)
IPDif			−0.132* (0.071)
MarkCapDif			−0.176*** (0.059)
VDAX			−0.017*** (0.001)
lnUS-Tbill			−0.264*** (0.014)
Number of observations	2184	2184	1938
Number of groups	91	91	91
Correlation (δ_i, x_i)	0.013	0.000	0.000
R^2	0.401	0.381	0.496
$F-value$ or $Wald-\chi^2_{(k)}$	25241.27*** <1%	23897.11*** <1%	2937.48*** <1%
Instrumented variable(s)	1st lag of *InterDif*	1st lag of *InfDif*	1st lags of *InterDif* and *InfDif*
Hausman ($\chi^2_{(k)}$) statistics	164.02*** <1%	−1080.75 >10%	−628.18 >10%

Notes: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parentheses indicate standard errors. $F-value$ and $Wald-\chi^2_{(k)}$ are joint test values for the FE and RE models, respectively. Instrumented variables used in the endogeniety bias test are the first lagged *InflationDifferentials* and *InterestRateDifferentials* variables. The coefficients in the RE and FE model are estimated by the SGLS (2stages GLS) IV and Fixed effect (within) IV methods, respectively.

To account for the dynamic cross sectional dependence (CSD) problem in the dynamic panel models in Table 5, we estimate the panel models with dynamic common correlated effects estimator (DCCEE) devised by Chudik and Pesaran (2015). Table 6 reports the results for the tests. We state that unlike Regression 3 in Table 5, Regression 3 in Table 6 exclude the VDAX variable for effective estimations. The high values (208.37, 183.58, 93.83) of the CD statistics in Regressions 1, 2, and 3 suggest the existences of the cross sectional dependences across cross sectional units where cause estimates from the linear dynamic panel specifications biased. Overall, the results for our main explanatory variables obtained from the dynamic panel models with DCCEE are qualitatively similar with ones obtained from the linear dynamic panel models in Table 5. Some exceptions are on the insignificant interest rate differentials-EMU and GIIPS slope dummies and marginally significant inflation differentials-Subprime dummy in Regression 3 and the significant inflation differentials in Regression 2, respectively. This suggests that our dynamic panel results for the main explanatory variables in Table 5 remain valid although we consider the dynamic CSD across cross sectional units for the dynamic panel models.

Table 5
Results of the linear dynamic panel regressions for European stock market integration.

Variables	Reg.1	Reg.2	Reg.3
Constant	1.124*** (0.047)	1.135*** (0.048)	1.406*** (0.065)
$Z\_Correlations_{t-p}$	Inclusive	Inclusive	Inclusive
D_{EMU}	0.598*** (0.056)	0.643*** (0.059)	0.780*** (0.060)
D_{GIIPS}	0.960*** (0.035)	0.967*** (0.023)	1.120*** (0.042)
$D_{Subprime}$	0.666*** (0.043)	2.044*** (1.037)	0.668*** (0.208)
InterDif	−0.032*** (0.006)		−0.023 (0.016)
$InterDif\_D_{EMU}$	−0.098*** (0.011)		−0.043** (0.019)
$InterDif\_D_{GIIPS}$	0.348*** (0.128)		0.159 (0.144)
$InterDif\_D_{Subprime}$	0.239*** (0.060)		0.253*** (0.059)
InfDif		−2.769 (0.734)	−0.433 (1.110)
$InfDif\_D_{EMU}$		−9.633*** (3.376)	−8.417*** (2.402)
$InfDif\_D_{GIIPS}$		6.295** (2.954)	−6.130*** (2.429)
$InfDif\_D_{Subprime}$		−470.5617 (348.138)	−81.112 (72.543)
IPDif			0.036 (0.079)
MarkCapDif			−0.131* (0.072)
VDAX			−0.018*** (0.001)
lnUS-Tbill			−0.253*** (0.011)
Number of observations	2275	2,275	2016
Number of groups	91	91	91
$Wald-\chi^2_{(k)}$	2040.00*** (1%<)	3241.61*** (1%<)	2924.96*** (1%<)

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Coefficients of all the panel regression models are estimated by the GMM method. Figures in parentheses indicate robust standard errors. The dynamic panel data models are fitted by Arellano and Bond (1991). All linear dynamic panel data models include lags (2) of the dependent variable as covariate and have unobserved panel (random or fixed) effects.

4.5. Robustness: A qualitative approach for integration of EU stock markets

Our analysis on integration of EU stock markets primarily depends on a quantitative approach of using comovement of EU stock markets measured by using realized moments technique with daily stock returns. A high degree of comovement among stock market stocks may be attributed to contagion or to cross-country risk differentials being insufficient reflected in financial markets where integration is actually low. This implies that financial integration needs to be assessed not only by a set of one quantitative indicator (i.e., price) but also by a set of quantitative and qualitative indicators.

For robustness, we investigate dynamic nature of EU stock market integration within a framework of a qualitative approach. To this end, inspired by Asdrubali and Kim (2004), we apply the linear dynamic panel regressions to distinguish contributions of credit market (interest rate) differences and relative price (inflation) differences to differences among country specific real GDP growth (output) shocks. To expurge any cyclical moments in country specific real GDP growth shocks, our study uses country specific real GDP growth shocks smoothed by the Hodrick and Prescott (1997)-filtering technique.[12] Table 7 presents the results for the linear dynamic panel regressions.

[12] As in the variables of panel data previously, the three types of the panel unit root test for the differentials of smoothed GDP growth shocks among sample countries significantly reject the null of unit root in level. The specific results are untabulated but available upon request.

Table 6
Panel regression results with dynamic common correlated effects estimator for the Z_Correlations.

Variables	Reg.1	Reg.2	Reg.3
Constant	1.235*** (0.046)	1.283*** (0.058)	0.880*** (0.089)
D_{EMU}	0.478*** (0.067)	0.535*** (0.048)	1.006*** (0.136)
D_{GIIPS}	0.949*** (0.037)	1.143*** (0.039)	−0.225 (0.279)
$D_{Subprime}$	−4.515*** (0.499)	0.780*** (0.056)	0.646*** (0.094)
InterDif	0.091***** (0.026)		−0.139*** (0.034)
*InterDif_*D_{EMU}	−0.242*** (0.080)		0.106 (0.113)
*InterDif_*D_{GIIPS}	0.231* (0.132)		0.260 (0.590)
*InterDif_*$D_{Subprime}$	−4.515*** (0.499)		−0.016 (0.087)
InfDif		1.975*** (3.557)	5.637 (3.630)
*InfDif_*D_{EMU}		−10.644** (5.626)	−27.314** (8.410)
*InfDif_*D_{GIIPS}		31.397*** (6.200)	112.516*** (45.857)
*InfDif_*$D_{Subprime}$		−6.700 (11.396)	−40.076* (23.009)
IPDif			0.087 (0.134)
MarkCapDif			−0.206 (0.193)
lnUS-Tbill			0.104*** (0.031)
Number of observations	2184	2093	1716
Number of groups	91	91	91
Cross sectional lags	1	2	1
Cross sectional dependence statistics	208.37	183.58	93.83
$F - value$	6.30*** (1%<)	12.21*** (1%<)	1.85*** (1%<)
R^2	0.90	0.92	0.92

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate standard errors.

No Regressions in Table 7 estimate significant value for the EMU intercept dummy and then suggest no direct effect of the EMU launch on the differences of the smoothed GDP growth shocks among sample countries. However, the EMU slope dummies interactive with the interest rate (credit market) differentials and inflation (relative price) differentials in Regressions 1 and 2 make interesting stories. Regression 1 estimates the significantly bigger negative estimate (−0.064) for the EMU slope dummy (*InterDif_*D_{EMU}) interactive with the interest rate differentials than the value (−0.054) of the simple interest rate differentials (*InterDif*). This result suggests that post EMU, the bigger interest rate differences led to the smaller GDP differences (i.e., bigger GDP similarities) among sample EU countries. This implies that lower economic growth countries could more effectively borrow capitals for financing investments from countries with lower interest rates due to an enlargement of a free flow of capitals among countries driven by the EMU wake. Thus, a greater flow of capital from countries of lower interest rate to ones of higher interest rate contributes to a decrease in the GDP differences among countries in Europe. The insignificant estimates on the GIIPS and Subprime slope dummies interactive with this variable in Regression 1 suggest no relation on the dependent variable. As for the effects of the GIIPS and Subprime intercept dummies, Regressions 1, 2 and 3 estimate significant negative values for both.

In association with the effects of the relative price differentials on the GDP shock differences, Regressions 2 and 3 make significantly positive coefficients (35.332, 20.928) for the inflation differentials (*InfDif*) at the 1% level, as expected. The results address that pre EMU, inflation differences make a positive relation with output differences among sample EU countries. By contrast, the EMU slope dummy (*InfDif_*D_{EMU}) interactive with this variable makes a totally different story. That is, Regressions 2 and 3 show the big negative coefficients (−18.077, −25.708) at the 1% level. This suggests that post EMU, greater inflation differences contribute

Table 7
Results of the linear dynamic panel regressions for differentials among smoothed GDP shocks of sample countries.

Variables	Reg.1	Reg.2	Reg.3
Constant	1.474*** (0.169)	0.881*** (0.227)	0.977*** (0.247)
$SmoothedGDP_{t-p}$	Inclusive	Inclusive	Inclusive
D_{EMU}	−0.093 (0.134)	−0.067 (0.203)	−0.077 (0.257)
D_{GIIPS}	−0.329*** (0.081)	−1.006*** (0.132)	−0.320*** (0.116)
$D_{Subprime}$	−0.158*** (0.101)	−4.426** (2.246)	−1.164*** (1.162)
InterDif	−0.054*** (0.030)		−0.146* (0.087)
*InterDif_*D_{EMU}	−0.064* (0.038)		0.132 (0.087)
*InterDif_*D_{GIIPS}	0.358 (0.379)		0.363 (0.635)
*InterDif_*$D_{Subprime}$	0.088 (0.109)		0.703** (0.246)
InfDif		35.322*** (7.981)	20.928*** (5.545)
*InfDif_*D_{EMU}		−18.077*** (7.737)	−25.708*** (9.934)
*InfDif_*D_{GIIPS}		70.733*** (8.902)	23.372* (12.702)
*InfDif_*$D_{Subprime}$		1180.574 (749.3819)	175.939 (88.777)
IPDif			−0.147 (0.100)
MarkCapDif			0.669*** (0.228)
VDAX			0.004*** (0.001)
lnUS-Tbill			−0.063*** (0.035)
Number of observations	2275	2275	2016
Number of groups	91	91	91
$Wald - \chi^2_{(k)}$	69.71 (1%<)	169.91 (1%<)	114.23 (1%<)

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. The GDP growth shocks of individual countries are smoothed by using the filtering technique of the Hodrick and Prescott (1997). Coefficients of all the regression models are estimated by the GMM method. All linear dynamic panel data models include lags (2) of the dependent variable as covariate and have unobserved panel (random or fixed) effects. Figures in parentheses indicate robust standard errors. The dynamic panel data models are fitted by Arellano and Bond (1991).

to a decrease in output differences among sample countries. One possible explanation for the counterintuitive finding would be due to a transfer of wealth from credit nations of low inflation countries to debtor nations of high inflation at the periods of the relatively low real interest rates with high inflations. This interpretation could be helpful for reducing discrepancies of investment and output among countries in Europe, a region with open economic structures among countries. However, this may cause a side effect of a bubble followed by rapid rises of real estate and asset prices, if the economic situation of relatively low interest rates in high inflation countries continues in a long term.

As for the GIIPS slope dummy interactive with the inflation differentials, we observe a positive effect of the relative price differences among countries, as Regressions 2 and 3 estimate significantly positive values for that. Comparatively, Regressions 2 and 3 estimate insignificant coefficients for the inflation differentials-Subprime slope dummy. This suggests no effect of the relative price differences on the GDP differences for pairs of sample EU countries during the Subprime crisis. Our qualitative analysis using differences of country specific smoothed output (GDP) shocks among countries suggests the significant effects of credit market and relative price differences on output differences among them after the EMU launch. Overall, these results are qualitatively in line with those from our quantitative approach using a price-based indicator of realized correlations of stock returns in Europe.

In regard to the effects of the control variables, Regression 3 in Table 7 estimate positive coefficients for the market capitalization differentials (*MarkCapDif*) and the financial market uncertainty (*VDAX*) but a negative one for the rate of the global risk free return

Table 8
Panel regression results with dynamic common correlated effects estimator for the smoothed GDP shock differentials.

Variables	Reg.1	Reg.2	Reg.4
Constant	0.984*** (0.263)	1.505*** (0.162)	1.135*** (0.220)
D_{EMU}	−0.149 (0.263)	−0.604*** (0.145)	0.029 (0.162)
D_{GIIPS}	0.144 (0.150)	−0.169*** (0.087)	0.780 (0.732)
$D_{Subprime}$	−0.339*** (0.092)	−0.416*** (0.087)	−0.193 (0.152)
InterDif	−0.081 (0.094)		0.036 (0.066)
*InterDif_*D_{EMU}	−0.125** (0.057)		−0.007 (0.076)
*InterDif_*D_{GIIPS}	0.084 (0.225)		−0.148 (0.425)
*InterDif_*$D_{Subprime}$	0.041 (0.081)		−0.047 (0.119)
InfDif		8.334** (4.268)	10.191*** (4.459)
*InfDif_*D_{EMU}		−21.826*** (5.689)	−25.222** (6.805)
*InfDif_*D_{GIIPS}		−18.673 (17.968)	−21.936 (46.476)
*InfDif_*$D_{Subprime}$		3.772 (5.180)	−0.062 (16.738)
IPDif			−0.110 (0.136)
MarkCapDif			−0.026 (0.166)
VDAX			0.003 (0.002)
lnUS-Tbill			−0.100*** (0.030)
Number of observations	1924	1924	1716
Number of groups	91	91	91
Cross sectional lags	1	1	1
Cross sectional dependence statistics	13.95	16.27	5.73
$F - value$	1.35*** (1%<)	1.25*** (1%<)	2.56*** (1%<)
R^2	0.73	0.62	0.92

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate standard errors.

(*lnUS-Tbill*). In particular, the significant positive estimate (0.669) for the *MarkCapDif* variable suggests a positive effect of the stock market development differences on the differences of the smoothed GDP growth shocks among countries. This implies that lower economic structure differences (i.e., higher similarities) proxied by the stock market capitalization differentials among countries are associated with lower differences of output differences.

To take into account the dynamic dependence across cross sectional units in Table 7, this study estimates the panel models with the dynamic common correlated effects estimator (DCCEE) of Chudik and Pesaran (2015). Table 8 reports the results from the panel estimations with the dynamic cross sectional dependence effects. Overall, our dynamic panel results for the main explanatory variables in Table 7 remain valid for the results from the panel estimations with the DCCEE in Table 8. Distinctive exceptions are on insignificant coefficients of the interest rate differentials in Regressions 1 and 3 and on insignificant ones of the inflation differentials-GIIPS slope dummy in Regressions 2 and 3. Qualitatively, the results reported for our explanatory variables in Table 8 are identical to ones reported in Table 7 as well.

Additionally, we test for the causality between EU stock market integration (i.e., realized correlations) and EMU by using the traditional pairwise Granger causality test. The Granger causality statistics for both variables strongly reject the nulls bilaterally and so, suggest a bilateral causality between EU stock market integration and EMU. Considering the time lags of the variables and size of the causality, our panel VAR test also estimates significantly positive coefficients (0.238 and 0.073) on the 1st lag of two variables bilaterally. Importantly, the VAR test results provide us with valuable information about the amount of the Granger causality between the two variables. That is, although both significantly make bilateral causal relationship each other, each endogenous explanatory variable shows different sizes of coefficients. The coefficient of the EMU_{t-1} variable (0.238) is much greater than that of the $Z\_correlations_{t-1}$ (0.073). The result suggests that EMU makes a stronger predicting power for integration of EU stock markets. The finding that EU stock market integration does also Granger cause EMU would be interesting in that EU stock markets could further progress toward a coupling by strengthening EMU. This may substantially contribute to an establishment of a good circulation between financial (stock) market development and stabilization of EMU in Europe.[13]

5. Conclusions

Focusing on the post EMU periods, this paper examines the impacts of the two contrasting events of EMU and GIPPS, and their monetary drivers on dynamic integration of EU stock markets. As a proxy of monetary performances convergence from EMU, we use two differentials of inflation and interest rate between fourteen EU countries. As a proxy of dynamic integration of EU stock markets, this paper employs time varying realized correlations among EU stock returns for a quantitative approach and differences of country specific smoothed GDP shocks for a quantitative one.

The panel data regressions with fixed or random effects suggest, after the EMU launch on 1st January 1999, a statistically significant increase in mean value of realized correlations of stock returns. Regarding the effects of the GIIPS crisis in 2010–2011, it also led to an increase in realized correlations of European stock returns. This result would be due to volatility spillover (i.e., contagion) effects during the crisis periods rather than due to return spillover effects. Our static and dynamic panel models also indicate a statistically significant increase in negative relationships between the realized correlations and monetary performance differentials (i.e., interest rate and inflation differentials) among sample EU countries since the EMU launch. The findings suggest strongly suggests that higher monetary similarities for pairs of EU countries have been a key driver for the increase in integration of EU stock markets since then. In perspective of a qualitative study, our dynamic panel analysis does not find a direct effect of EMU on economic output (i.e., GDP) convergence among EU countries. However, we find evidence that post EMU, higher monetary performance differences are associated with lower economic output (i.e., GDP) differences among EU countries. This finding is qualitatively in line with that of our quantitative study using comovement (i.e., realized correlations) with a price-based indicator for studying integration of EU stock markets. Overall, these empirical results support the theoretical expectation discussed in this study.

It seems that effective reforms of macroeconomic policy exert significant effects on the behaviour of investors in the EU stock markets. Thus, our study has invaluable implications for investors' diversification and for policymakers' conduction of a single monetary policy in Europe. In addition, this study targeting mostly western and northern EU countries could provide us with meaningful implications or lessons regarding the process of convergence of recently emerging central and eastern EU stock markets (Simon, 2005; Van Beek et al., 2000 among others). Some limitations should be mentioned. This paper focuses on the dynamic process of integration of European stock markets in a country level. It would be worthwhile to examine nature and drivers of time-varying integration of EU stock markets in an industry or a firm level.

CRediT authorship contribution statement

Hyunchul Lee: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Writing - original draft, Writing - review & editing. **Heeho Kim:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Writing - review & editing.

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[13] The specific results for this test are untabulated to consider space but are available upon request.

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