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Which are the long-run determinants of US outward FDI? Evidence using large long-memory panels*

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Abstract

This paper analyzes the long-run determinants of US outward FDI stock, focusing mainly on the Euro Area (EA) for the period 1985-2019. We consider a sample of 54 developed and emerging host countries representing over 70% of the total US outward FDI stock. We aim to capture different determinants by country groups zooming in on the European Union (EU). We implement a Dynamic Common Correlated Effects Pooled Mean Group (DCCEPMG) estimator for this aim. Our econometric approach is especially suited for analyzing integrated economic areas as it allows us to deal with cross-section dependence (CSD), non-stationarity, structural breaks, and slope homogeneity usually present in large panel data. Our main results suggest that horizontal (HFDI) and vertical (VFDI) strategies coexist for all country groups. However, as we move towards more homogeneous groups, the results show greater importance of VFDI. Additionally, we find that some variables have a common long-run effect on US OFDI, especially for smaller and more homogeneous groups.

Keywords: BMA, DCCEPMG, long-run, structural breaks, economic integration.
JEL classification: F21; F23; R39.

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1 Introduction and motivation

In this paper, we analyze the long-run determinants of the stock of outward US FDI (OFDI) with a particular focus on the European Union (EU). Our empirical approach aims to efficiently account for the effects that the different steps in the process of economic integration in the EU has had on US outward FDI. Uncovering the reasons that attract FDI to the EU is a difficult task. Aristotelous and Fountas (1996) or Kim (2004), find that firms outside the EU invest in the union due to multiple reasons. First, to avoid trade barriers and take advantage of a larger market size. This strategy is known as horizontal FDI (HFDI). Second, internal FDI increased with the creation of the Single Market, due to the significant differences in labour costs and relatively short supply chains.[1] This motivation, known as vertical FDI (VFDI) is especially relevant in the new Central and Eastern member states (Bevan and Estrin, 2004). Moreover, both HFDI and VFDI strategies may coexist[2] within the EU, as pointed out by Dorakh (2020) and Dauti (2016).[3]. Finally, some external shocks, as the introduction of the common currency in 1999 or the Great Recession in 2008 may have affected the process of economic integration in terms of trade and FDI. While the Euro effect has been more deeply studied[4], the second still deserves further attention and call for an analysis that accounts for possible structural breaks in the series.

Although the EU has been the most prominent recipient of US FDI (European Comission, 2019), for the sake of comparison, we also study a large group of countries from different continents that receive US FDI. In particular, our sample contains the stock of US OFDI in 54 developed and emerging countries from 1985 to 2019, which represents over the 70% of the total US OFDI stock in 2019.[5] Furthermore, we focus on EU and EA countries separately. Additionally, within the EA, we distinguish between the core and the periphery. In the core,

[1] See Carril-Caccia and Pavlova (2018), Bruno et al. (2017), Straathof et al. (2008) and Bruno et al. (2021), among others.

[2] See the knowledge capital model of Carr et al. (2001).

[3] The expansion and complexity of the production fragmentation across border via Global Value Chains (GVCs) has led Yeaple (2003) to coin the FDI generated by these mixed motives as "complex FDI" and more recently Baldwin and Okubo (2014) have developed the concepts of "horizontal-ness" and "vertical-ness" to systematically account for these more complex forms of FDI.

[4] See Carril-Caccia and Pavlova (2018), Petroulas (2007), De Sousa and Lochard (2011), Brouwer et al. (2008) Baldwin et al. (2008), Neary (2009), and Sondermann and Vansteenkiste (2019), among others.

[5] Most FDI has accumulated in the EU and in the North American Free Trade Agreement (NAFTA), each of them representing percentages close to 30%. The other main recipients are the Association of Southeast Asian Nations (ASEAN) and Japan, China, and the Republic of Korea (ASEAN plus Three), and Mercado Común del Sur (MERCOSUR).

we include Germany and its immediate neighboring Eurozone countries, whereas in the periphery are those EA countries that are farther from the center, that is, those of Northern and Southern Europe.[6] These differences are also evident in the spatial distribution of US OFDI in the EU in 2019 in the map of Figure 1. The main recipients of US FDI are those in the core of the EU: the United Kingdom (UK), and some Eurozone member states, such as the Netherlands, Germany, and France. As for the periphery, Ireland, followed by Spain, Italy and Sweden stand out. Finally, US FDI has been modest in Portugal, Greece, and Central and Eastern European countries. The breakdown of the countries in the area into smaller and more homogeneous groups will help us to identify similar characteristics to explain the different behavior of US OFDI in EU countries.

We apply a version of the gravity model to approximate the cross-country patterns of US OFDI stock in the long run, as it has proved to be solid not only to provide a good fit of the data but as a theoretical foundation. The earliest and most influential theoretical contributions include Bergstrand and Egger (2007), and Head and Ries (2008), who derived general equilibrium theories for FDI. Later, Kleinert and Toubal (2010) showed that gravity equations could be used to discriminate between different theoretical approaches. Finally, Yotov et al. (2016) and Anderson et al. (2017, 2020) are more recent developments in the literature that set the ground for structural gravity models.

Most of the previous empirical literature that studied FDI determinants did not consider the non-stationary properties of the series and failed to account for structural breaks in the long-run relationship between the variables. Moreover, the analysis of an economically integrated area as the EU can be improved using panel data, as it enriches the information included in the analysis. Nonetheless, panel data present a series of econometric issues, many times neglected in empirical applications, such as the existence of observed and unobserved common effects, CSD and parameter heterogeneity[7]. Precisely, the salient feature of our econometric approach is that it allows us to exploit both the cross-section and the time-series information included in large long-memory panels, aspects commonly disregarded previously. Our empirical approach looks at three elements: long-run relationships, the paths toward the long-run equilibrium after a shock (break), and the short-run

[6] This division is based not only on geographical criteria but also on economic similarities. Indeed, Bayoumi and Eichengreen (1993), Zhang and Artis (2001) and Konstantakopoulou and Tsionas (2011), among others, found that this classification could be based on business cycles synchronicity and common economic shocks.

[7] See, among others, Pesaran (2006), Eberhardt and Bond (2009), Chudik and Pesaran (2015), and Ditzen (2018).

impact. Additionally, one of our primary motivations is the search for similarities across country groups in the long-run. In order to handle dynamic and homogeneous coefficients of a panel model that incorporates lagged dependent and weakly exogenous regressors, we use the DCCEPMG estimator. The DCCEPMG is a modified estimator that combines the Dynamic Common Correlated Effects approach (DCCE hereafter) due to Chudik and Pesaran (2015) with the Pesaran et al. (1999) Pooled Mean Group (PMG hereafter) estimator. In addition, we extend this estimator to allow for the existence of common structural break endogenously detected.

We contribute to the empirical literature on FDI in several respects. First, instead of just focusing on a specific regression model and an *ad hoc* gravity setting, we build on Camarero et al. (2021) to select the incumbent drivers of our empirical model, drawing on their Bayesian Model Averaging (BMA) analysis. Second, to measure the potential long-run effects of the main economic events of our sample period (such as the establishment of the Single Market, the successive EU enlargements, the inception of the euro, or the 2008 financial crisis) we use the Banerjee and Carrion-i Silvestre (2015) approach to endogeneously detect structural breaks in the long-run relationships, and test for potential changes in the parameters after these events. Lastly, we focus both on the magnitude and effect of the long-run drivers of US OFDI and on which of them have a homogeneous effect. For this purpose, in addition to the larger group (the 54 countries in our sample) we also study smaller groups of countries with economic meaning within the EU, looking for more homogeneous determinants in each group.

Our main results are, first, that similar drivers attract US FDI to the country groups we analyze, although the strategies followed have been different and, sometimes, have changed during the sample period. Those structural breaks, as we expected, are related not only to external events (such as the world financial crisis) but also to institutional changes within the EU, such as the creation of the euro or the 2004 enlargement to the East. Second, we have found long-run relationships linking FDI and its drivers for all country-groups once we account for the structural breaks and allow for a combination of homogeneous and heterogeneous parameters in the specification. Third, both horizontal and vertical strategies coexist in all country groups. However, as we move towards more homogeneous groups, VFDI prevails. Finally, some of the relevant variables have homogeneous parameters in the specifications. As one may expect, this fact is especially evident in smaller and more homogeneous country-groups.

The remainder of the paper is organized as follows: in Section 2 we briefly review the econometric methodology adopted as well as its rationale and previous empirical literature following this approach; Section 3 describes the theoretical model, as well as the data and the specification of the empirical model; Section 4 presents a summary of the econometric methodology and our empirical results, and finally, Section 5 concludes.

2 A brief review of the related empirical literature

2.1 Large-N and Large-T properties of panel data estimators

In this paper we follow recent advances in panel time series models to efficiently estimate a gravity specification of the determinants of the US OFDI to the EU. Estimating panels with heterogeneous coefficients with a large dimension of observations over cross-sectional units (N) and time periods (T) has become the new standard, both thanks to seminal works in theoretical econometrics (Pesaran and Smith, 1995; Pesaran et al., 1999) and also to the increasing availability of data. Panel time series models combine the best from panel data and time series, namely, they account for classical time series topics (unit roots, stationarity, cointegration), together with dependence over time, cross-section dependence (CSD), slope heterogeneity and structural breaks. Not accounting for unobserved dependence between cross-sectional units causes the error term to be autocorrelated and leads, in ordinary least-squares (OLS) regression, to biased results. Moreover, the longer the time span, the higher the likelihood of changes in the model parameters as a result of major disruptive events. Detecting the existence of breaks, and dating them is, therefore, necessary not only for estimation purposes but also for understanding the drivers of change and their effect on economic relationships.

There is a vast literature that studies the relative importance of alternative FDI determinants from several theoretical standpoints and using a myriad of econometric techniques, both in panel data and time series. Panel data with a large number of time-series observations have been increasingly available in recent years in many economic fields such as international finance and trade. It is now common to have panels in which not only N (the number of groups) but also T (the range of time periods) are relatively large. Consistent with this trend, some recent studies have examined the large-N and large-T properties of the within and GLS estimators in models.[8]

While early panel literature assumed that errors were cross-sectionally independent and slopes homogeneous, with both large N and T, these two assumptions cannot be, in most cases, maintained. In this section, first, we briefly review the different approaches and procedures applied to macroeconomic time series with panel data when the members of the panel exhibit CSD. Second, we also survey how to test for homogeneous slopes and describe methodological approaches that accommodate long-run homogeneity and short-run heterogeneity, which are more realistic assumptions. The purpose of this revision is not only to describe the context of our research but also the advantages of the approach we follow. Finally, we revise the findings of other empirical papers that have also used a similar methodology to study the long-run determinants of FDI.

According to Chudik and Pesaran (2014), conventional panel estimators (such as fixed or random effects) do not account for CSD, which may result in erroneous inference or even inconsistent estimators. When the parameter of interest is the average effect of some exogenous variable on a dependent variable, numerous papers have employed dynamic models to estimate long-run relationships in panel data. The pooled estimator is the most frequently used procedure to estimate this average effect, which combines the data by imposing homogeneous slopes, allowing for fixed or random intercepts. However, Pesaran and Smith (1995) shows that the pooled estimator is not consistent in dynamic models (because when the regressors are serially correlated, incorrectly ignoring coefficient heterogeneity induces serial correlation in the disturbance term, which generates inconsistent estimates. Consequently, they propose the mean group estimator (MG), which estimates separate regressions for each group and averages the coefficients over those groups. Later, Pesaran et al. (1999) combined both the pooled and MG estimators. The latter is known as the PMG estimator, where all or some of the long-run coefficients are allowed to be the same across units, whereas the short-run coefficients differ[9].

As mentioned above, CSD across units can lead to biased results if ignored. The latter is particularly important in our case, as our panel data set contains 54 countries, including EU countries, members of a highly integrated area, that share common shocks and for which the existence of CSD is more than expected. Breusch and Pagan (1980) propose a

[8] For example, Phillips and Moon (1999) and Kao (1999) establish the asymptotic normality of the within estimator for the cases in which regressors follow unit root processes.

[9] This is the estimator that we use for the estimation of the long-run determinants of US OFDI stock

method to detect CSD based on the average of the squared pair-wise correlation of the residuals. However, this test is likely to exhibit substantial size distortions when N is large and T small. Alternatively, the Pesaran (2004) test has reasonable small sample properties under the null hypothesis of zero CSD. Nonetheless, this assumption is quite unrealistic, and therefore, later Pesaran (2015) proposed a new test for the hypothesis that errors are weakly cross-sectionally dependent.

We can use several alternative approaches to deal with CSD in model estimation. A first possibility is the use of spatial techniques [10] when the source of correlation is related to the distance between the units.[11] A second option is the use of common factor models, that implies the use of a common factor specification with a fixed number of unobserved factors[12]. However, Pesaran (2006) demonstrates that this procedure is inconsistent if the unobserved factors and the regressors are correlated. Alternatively, he proposes the Common Correlated Effect (CCE) estimator. It consists of filtering the individual-specific regressors utilizing cross-section averages. One advantage of this estimator is that it can be computed easily by least squares adding to the regression the cross-sectional averages of the dependent and independent variables. As a step forward, Chudik and Pesaran (2015) extends this procedure to heterogeneous panel data models with lagged dependent variables and weakly exogenous regressors. It is known as the DCCE estimator, and it can also be implemented by least squares adding to the regression the cross-sectional averages of the dependent and independent variables and their lags. The latter is the approach adopted in this paper, as we estimate dynamic error correction models with the PMG estimator of Pesaran et al. (1999), augmented by the cross-section averages and their lags, the so-called Dynamic Common Correlated Effects Pooled Mean Group (DCCEPMG) estimator. This estimator is employed because it is robust to endogeneity, slope heterogeneity and correlations in residual terms (Chudik and Pesaran, 2015; Ditzen, 2018).

Chudik and Pesaran (2014) point out, the presence of correlation across units in panels also

[10] See Lee and Pesaran (1993), Conley and Topa (2002), Conley and Dupor (2003), Pesaran et al. (2004) and Dées et al. (2005), among others.

[11] When the cross-section dimension is short, and the time-series dimension is long, the standard approach to dependence is to treat the equations from the different cross-section units as a system of seemingly unrelated regression equations (SURE) and then estimate the system by generalized least squares (GLS) techniques (See Holtz-Eakin et al. (1988), Ahn et al. (2001), Kiefer (1980) and Lee (1991).). Nevertheless, in the first case, a distance measure is not always available, while the SURE-GLS approach involves nuisance parameters as the cross-section dimension of the panel increases (and becomes non-feasible when $N > T$). Moreover, the SURE estimator would not be consistent if the source of CSD is correlated with the regressors.

[12] See Robertson and Symons (2000), Coakley et al. (2002) and Phillips and Sul (2003).

has essential effects on unit root tests, as many of them initially assumed independence. Therefore, it is crucial to account for cross-correlation first in the order of integration analysis of the variables and later during the estimation of the models. O'Connell (1998) found out that when we use unit root tests assuming independence in cross-sectional dependent panels, such tests have substantial size distortions. In the case of unit root tests, the common practice was to de-mean the series. However, when the pair-wise cross-section covariances of the error terms differ across the individual series, this would not work. As an alternative, some used a nonlinear instrumental variable approach (such as Chang (2002), in a two-way error-component model where they imposed the same pair-wise error covariances across units), while others employed residual factor models (Bai and Ng, 2004; Moon and Perron, 2004). Later, Pesaran (2007) proposed a simpler alternative test where the cross-section averages of lagged levels and first differences of the individual series are added to the standard augmented Dickey-Fuller (ADF) regressions (CADF). Subsequently, the individual CADF statistics have been used to define modified versions of the t-bar test proposed by Im et al. (2003) (IPS), such as the CIPS test.

In the context of panel cointegration, to estimate a dynamic error correction model, accounting for dependence may not be enough. When the time dimension of panels becomes large, the likelihood of one or several variables having structural breaks increases. In our analysis, the US outward FDI sample goes from 1985 until 2019, a period when several crises have occurred and during which the European countries have immersed in a process of deep economic integration. For this reason, the approach that we adopt will allow for structural breaks not only in the analysis of the order of integration of the variables but also in the long-run relationships.To this aim we use the panel unit root test proposed by Bai and Carrion-i Silvestre (2009), which simultaneously accounts for CSD and structural breaks. Similarly, to test for long-run relationships, we apply the Banerjee and Carrion-i Silvestre (2015) cointegration test, that also allows for both structural breaks and CSD[13]. Finally, we estimate heterogeneous coefficient models using common correlated effects in a dynamic panel using the DCCEPMG estimator.

[13]In contrast to Kao and Chiang (2000), Banerjee and Carrion-i Silvestre (2004), Westerlund (2006) or Gutierrez (2010), that assumed independence across units.

2.2 A review of the recent empirical literature on FDI determinants using Pooled Mean Group estimators

A few previous papers have studied the long-run FDI determinants of FDI using PMG estimators. In order to review their results, we classify them by region. We start with some papers that have studied African countries. Abdelbagi et al. (2016) study FDI inflows in Africa during the period 1974-2013. Their findings suggest that the main determinants are economic growth, human capital, infrastructure, domestic investment, and the region's trade openness. Similarly, Boğa (2019) for Sub-Saharan Africa and a slightly more extended period (1975-2017) find that GDP growth, trade openness, domestic credit, natural resources, and telecommunication infrastructure are the most important determinants. Fofana et al. (2018) investigate the relationship between FDI inflows, economic growth, and exports in West African countries in the period 1980 - 2014. They find that economic growth attracts foreign investment and exports in the long run. Furthermore, Ren et al. (2012) study the effect of institutional variables on MENA[14] countries for the period 1984 - 2009, revealing that institutional quality attracts FDI inflows.

Other papers also use the PMG estimator to study the long-run FDI determinants in Asian regions. For example, Behera et al. (2020) assess the impact of institutional quality on FDI inflows between 2002 and 2016 for South Asian countries and find a long-run relationship. Similarly, Jalil et al. (2016) investigated the effect of corruption on foreign investment inflows in 42 countries in Asia, Africa, and Latin America from 1984 to 2012. Their findings reveal that corruption has a positive impact on FDI in the case of Asia and Africa, but the opposite is true for Latin America. Moreover, Othman et al. (2018) studied the impact of government spending on FDI inflows for ASEAN-5 countries, China and India, from 1982 until 2016 and also found a long-run positive effect.

In the case of the BRICS[15] countries, Azam and Haseeb (2021) examine the impact of different types of energy sources on FDI inflows over the period 1990 - 2018. They find that the effect of renewable energy utilization on FDI is more significant than the non-renewable one in the long run. Moreover, Maryam and Mittal (2020) study the macroeconomic factors that affect foreign investment inflows in the BRICS from 1994 to 2018. Their results suggest that GDP, trade openness, the exchange rate, gross capital formation, and the availability

[14] the Middle East and North Africa
[15] Brazil, Russia, India, China, and South Africa

of infrastructure facilities are significant in the long run.

Finally, the PMG estimator has also been used to analyze FDI determinants in EU countries. Albulescu and Ianc (2016) study the long-run relationship between FDI inflows and the financial environment in 16 EU countries. Their results point out that monetary uncertainty reduces FDI inflows. On the other hand, banking stability attracts foreign investment and finds a positive relationship between the business cycle and inward FDI. Finally, Su et al. (2018) study the effect of some macroeconomic factors on FDI inflows in Visegrad[16] group countries after the EU enlargement in 2004. Whereas corruption deters FDI in Poland, the Czech Republic, and Slovakia, human resources and exports play a major role in attracting FDI for Hungary.

However, to the best of our knowledge, there are not applications that estimate FDI determinants accounting jointly for non-stationarity of the series, CSD, slope heterogeneity and structural breaks. In the present research we aim to fill this methodological gap using state of the art econometrics for large long memory panels.

3 Theoretical approach, data and empirical model

In this section, we describe the empirical approach adopted and database. We use stock data[17] for the period 1985-2019 and adopt the methodology that better captures the complexity of this topic. In particular, we account for CSD in an international context where the trade and investment relationships have evolved and intensified with time. In addition, the large degree of heterogeneity among the US OFDI destinations makes quite unrealistic imposing long-run homogeneity in all the estimated parameters. Therefore, we use the DCCEPMG estimator.

In order to choose between competing theoretical approaches of FDI drivers, we estimate a gravity equation. We start from the theoretical Kleinert and Toubal (2010) horizontal model where firms can serve the foreign market j either by producing abroad or by exporting. The gravity equation estimated by Kleinert and Toubal (2010) is as follows:

$$AS_{i,j} = s_i(\tau D_{i,j}^{\eta^1})^{(1-\sigma)(1-\in)} m_j \tag{1}$$

[16] Poland, the Czech Republic, Slovakia, and Hungary.

[17] We use stock data instead of flows because they are more persistent and reliable along time. Therefore, it is a better measure to study the long-run FDI determinants.

where AS_{ij} are aggregate sales of foreign affiliates from firm i in j; s_i and m_j denote home and host country's market capacity, respectively, and $\tau D_{ij}^{\eta^1}$ stands for geographical distance between i and j where τ represents the unit distance costs and $\eta_1 > 0$.
Equation 1 can be log-linearized as

$$ln(AS_{i,j}) = \alpha_1 + \zeta_1 ln(s_i) - \beta_1 ln(D_{i,j}) + \xi_i ln(m_j) \quad (2)$$

This type of expression is the one commonly used in the gravity models for FDI. Initially, market size and distance were the variables included in this type of models. However, with the evolution of the FDI literature others have been added such as labour market conditions, trade, institutional quality, technology development and macroeconomic instability. We start from the variables considered robust to explain FDI in Camarero et al. (2021), who use BMA analysis. As there are multiple potential candidate variables, we divided them in groups, such as market size and population, labour market, and trade and international openness. Once the robust variables within each group were identified, we select those for which we find a cointegration relationship. The robust determinants related to these groups are shown in Table 1, and the chosen variables[18] for each of them are marked in red. A detailed description of the selected covariates is available in Table 2. From market size and population, the variable chosen is **GDP** or *lgdp* for all country groups. In the case of the labour market covariates, those selected are **population density** or *lpod* for the whole group and EA periphery, **total factor productivity** or *tfp* for EU countries, and **labour compensation** or *labc* for the EA group and core countries. Finally, concerning trade openness, we include **trade openness** or *trdo* for the whole and EA core groups, **revenue from trade** or *rtrd* for the EU countries, and **mean tariff rate** or *mtrt* for the EA and periphery groups.

Our analysis starts in a panel that includes all the countries, in our case 54, with data available for the sample period (1985 - 2019). Then, we study separately the EU and the Eurozone groups and, finally, within this group, core and peripheral countries. The list of countries and the different groups considered are detailed in Table 3. We analyze groups including a smaller number of countries looking for similar characteristics and trying to capture similarities (homogeneity) that are somewhat hided in larger groups of countries.

[18]From the set of variables selected a robust in the BMA analysis, some of them cannot directly translated into the cointegration analysis. These are notably dummies, that will be indirectly accumulated in the country fixed effects or captured by the structural breaks.

The variables chosen slightly differ depending on the group of countries analyzed, as the results of the BMA analysis detected different robust determinants for each country group[19]. Therefore, our empirical model can be written as:

$$lusofdi_{i,t} = \theta_0 + \theta_1 x_{i,t} + \epsilon_{i,t} \tag{3}$$

where $x_{i,t}$ is the vector of explanatory variables, and θ_0 and θ_1 are the long-run coefficients. In the next section we describe the main econometric tools applied as well as the empirical results for the different groups of countries.

4 Econometric methodology and results

4.1 Cross-section dependence

Due to the composition of our database, prior to the specification and estimation of the models, we need to test for the existence of CSD because in case it is detected, all the subsequent analysis should take it into account. To begin, we apply the Pesaran (2004) test.

4.1.1 Pesaran (2004) cross dependence test

Consider the following panel data model

$$y_{i,t} = \alpha_i + \beta_i' x_{i,t} + u_{i,t} \tag{4}$$

where $i = 1, ..., N$ is the cross-section, dimension, $t = 1, ..., T$ is the time series dimension and $x_{i,t}$ is a $k \times 1$ vector of observed time-varying regressors. The individual intercepts, α_i, and the slope coefficients, β_i, are allowed to vary across i. For each i, $u_{i,t} \sim \left(0, \sigma_{iu}^2\right)$ for all t, although they could be cross-sectionally correlated. The dependence of $u_{i,t}$ across i could arise in a number of different ways[20].

Pesaran (2004) proposes the CD statistic, based on the pair-wise correlation coefficients instead of their squares, as in the LM test by Breusch and Pagan (1980), that has substantial

[19] Moreover, using several variables that capture the same effect would generate multicolinearity in the empirical model. We are also limited by the degrees of freedom, so that we choose one representative (robust) variable from the different categories described in Table 1.

[20] It could be due to spatial dependence, omitted unobserved common components, or idiosyncractic pair-wise dependence of $u_{i,t}$ and $u_{j,t}$ $(i \neq j)$ with no particular pattern of spatial or common components

size distortions for N large and T small.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{i,j} \right) \tag{5}$$

where $\hat{p}_{i,j}$ is the sample estimate of the pair-wise correlation of the residuals. The null hypothesis (H_0) is zero CSD, $Cov(u_{i,t}, u_{j,t}) = 0, \text{ for all } t, i \neq j$, against the alternative (H_1) that there is CSD.

The results of the test are presented in the first part of table 4. We include a maximum of 2 lags. As expected, the null hypothesis of no CSD is rejected at 1% significance levels for all the variables.

4.1.2 Pesaran (2015) cross dependence test

According to Pesaran (2015), the null of weak CSD seems more appropriate than the null of cross-sectional independence in the case of large panel data models where only pervasive cross-dependence is of concern. The latter seems especially suited to our case, where the time and cross-section dimensions are similar. Moreover, when the number of units is smaller (as in the EA), we consider countries of the same currency union, and cross-dependence would be expected. Therefore, we also compute the weak CSD test:

$$CD = \sqrt{\frac{TN(N-1)}{2}} \hat{\bar{p}}_N \tag{6}$$

where

$$\hat{\bar{p}}_N = \frac{2}{N(N-1} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{i,j} \right) \tag{7}$$

is the the average pairwise error correlation coefficient.

The results are presented in the second part of Table 4, where the null hypothesis of weak CSD is clearly rejected at 1% level of significance.

Therefore, after applying the two tests, we can conclude that there is CSD in our panel. Consequently, we control for it in the estimation by the inclusion of the cross-section averages of all the variables and their lags in the regressions. According to Chudik and Pesaran (2015), the number of lags should be equal to $\sqrt[3]{T}$, which in our case would be $\sqrt[3]{35} \simeq 3$. Taking into account that our variables are annual, we choose two lags of the cross-sectional averages.

4.2 Order of integration of the variables

The next step is to assess the order of integration of the variables. Non-stationarity is a necessary condition for cointegration, and consequently, for the existence of a long-run relationship among the variables. As we have found CSD, we apply panel unit root tests that account of it. The first panel unit root test that we apply is the CIPS statistic proposed by Pesaran (2007), following the logic of the previous section, and allowing for CSD.

4.2.1 Pesaran (2007) panel unit root test

Let $y_{i,t}$ be the observation on the ith cross-section unit at time t and suppose that it is generated according to the simple dynamic linear heterogeneous panel data model

$$y_{i,t} = (1 - \phi_i)\mu_i + \phi_i y_{i,t-1} + u_{i,t}, \tag{8}$$

where the initial value, $y_{i,0}$, has a given density function with a finite mean and variance, and the error term, $u_{i,t}$, has a single-factor structure, $u_{i,t} = \gamma_i f_t + \varepsilon_{i,t}$, where f_t is the unobserved common effect, and $\varepsilon_{i,t}$ is the individual-specific (idiosyncratic) error.

It is convenient to write (8) as

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{i,t} \tag{9}$$

where $\alpha_i = (1 - \phi_i)\mu_i$,$\beta_i = -(1 - \phi_i)$ and $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$. The unit root hypothesis of $\phi_i = 1$, can now be expressed as

$$H_0 : \beta_i = 0 \text{ for all } i \tag{10}$$

against the possibly heterogeneous alternatives,

$$H_1 : \beta_i < 0, i = 1, 2, ..., N_1, \beta_i = 0, i = N_1 + 1, N_1 + 2, ..., N \quad (11)$$

Following Pesaran (2006), the common factor f_t can be proxied by the cross-section mean of $y_{i,t}$, namely $\bar{y}_t = N^{-1} \sum_{j=1}^{N} y_{j,t}$, and its lagged value(s). Therefore, the test of the unit root hypothesis of (10) should be based on the t-ratio of the OLS estimate of $b_i(\hat{b_i})$ in the following cross-sectionally augmented DF (CADF) regression:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \epsilon_{i,t} \quad (12)$$

Subsequently, the individual CADF statistics are used to obtain modified versions of the t-bar test proposed by Im et al. (2003), such as the CIPS test. Our results for the CADF test are presented in the first part of Table 5. Also in this case, we allow for a maximum of 2 lags. In general, the null hypothesis of unit root is not rejected. Two exceptions are the **logarithm of the population density** or *lpod* with 1 lag at 1%, and **logarithm of US OFDI** or *lusofdi* with no lags at 5%.

4.2.2 Bai and Carrion-i Silvestre (2009) panel unit root test

When testing for unit roots, it is also important to allow for the possible existence of structural breaks, as external events may cause instabilities in the variables. According to Perron (1989), this is non-trivial, as unit root tests can lead to misleading conclusions if structural breaks are present but not accounted for. For this purpose, we apply Bai and Carrion-i Silvestre (2009) panel unit root test. They propose a set of panel unit root statistics that pool the modified Sargan-Bhargava (MSB) tests (Sargan and Bhargava, 1983) for individual series, taking into account the possible existence of multiple structural breaks. Moreover, this test allows for CSD as a common factors model, as described in Bai and Ng (2004) and Moon and Perron (2004). The common factors may be non-stationary processes, stationary processes or a combination of both. Their number is estimated using the panel Bayesian information criterion proposed by in Bai and Ng (2002).

Bai and Carrion-i Silvestre (2009) consider the following general panel data model:

$$X_{i,t} = D_{i,t} + F_t' \pi_i + e_{i,t} \quad (13)$$

where $D_{i,t}$ denotes the deterministic part of the model, F_t is an $(r \times 1)$ vector that accounts for the common factors of the panel, and $e_{i,t}$ is the idiosyncratic disturbance term.

Regarding the deterministic component $D_{i,t}$ in equation (13), Bai and Carrion-i Silvestre (2009) consider two models, Model A, where multiple structural breaks occur in the intercept, and B, where multiple structural breaks occur in the intercept and the time trend.

The objective of pooling individual MSB test statistics is to increase power. The null hypothesis is the following:

$$H_0 : \rho_i = 1 \;\; \forall i = 1, ..., N \tag{14}$$

against the alternative:

$$H_1 : |\rho_i| < 1 \;\; \text{for some} \;\; i. \tag{15}$$

Under the null hypothesis, all the idiosyncratic errors $e_{i,t}$ are $I(0)$. For any pooled test to have power, there should exist a strictly positive fraction of series that are I(0). The individual MSB statistic for each i is denoted $MSB_i(\lambda_i)$. This notation is used to reflect the dependence on the break point λ.

Bai and Carrion-i Silvestre (2009) show that the individual $MSB_i(\lambda_i)$ are asymptotically invariant to mean breaks (Model A). However, this invariance does not carry over to breaks in linear trends (Model B), where the test statistics will converge to a weighted Brownian bridge. Therefore, they propose a simplified test statistic $MSB_i^*(\lambda_i)$.

Bai and Carrion-i Silvestre (2009) apply the approach proposed by Maddala and Wu (1999) and Choi (2001) to combine individual test statistics in a panel test, that pools the p-values associated with the individual tests. These p-values are denoted p_i , $i = 1, ..., N$. Maddala and Wu (1999) defined P, the Fisher-type test statistic designed for fixed N, which follows a chi-squared distribution. Bai and Carrion-i Silvestre (2009) denote P^* the corresponding P statistic that is computed using the p-values of the simplified MSB statistic. Choi (2001) proposed the P_m test when $N \to \infty$. The P_m test is suitable for large N panels. As above, use P_m^* to denote the corresponding P_m statistic that is computed using the p-values of the simplified MSB statistic.

The results of Bai and Carrion-i Silvestre (2009) panel unit root tests are shown in the lower part of Table 5. We apply model B, where multiple structural breaks may occur in the intercept and time trend, with a maximum of 2 breaks, determined using the Liu et al. (1997) procedure. We apply the simplified version of the P and P_m test's statistics, because as mentioned above, this is the most suitable for the trend break model. In this case, the null hypothesis of unit root cannot be rejected for any of the variables.

Therefore, according to the results of the panel unit root tests, once the existence of CSD and structural breaks have been taken into account, we can conclude that our variables are non-stationary. Consequently, we can test for cointegration and estimate the long-run parameters.

4.3 Panel cointegration with structural breaks

When the time-series dimension of the panel is large, as it is in our case, we should account for structural breaks. Working with 35 annual observations, we cannot discard potential changes in the role or intensity of the explanatory variables in the framework of cointegration. Such shifts can be related with institutional changes, such as the establishment of the EU Single Market, the successive EU enlargements and the launching of the euro, or external events, as is the case of the 2008 crisis. Moreover, we have already detected the presence of structural breaks in the panel unit root tests. Therefore, we have to account for these shifts when testing for cointegration. For this purpose, we use the Banerjee and Carrion-i Silvestre (2015) test, which allows for both structural breaks and CSD when testing the null hypothesis of no cointegration.

Let $Y_{i,t} = (y_{i,t}, x'_{i,t})'$ be an $(m \times 1)$ vector of non-stationary stochastic processes whose elements are individually $I(1)$. The data-generating process (DGP) is specified as follows:

$$y_{i,t} = D_{i,t} + x'_{i,t}\delta_{i,t} + u_{i,t} \tag{16}$$

$$u_{i,t} = F'_t\pi_i + e_{i,t} \tag{17}$$

F_t denotes a $(r \times 1)$ vector containing common factors affecting $y_{i,t}$, being π_i the vector of loadings. The deterministic component $D_{i,t}$ is given by

$$D_{i,t} = \alpha_i + \phi_i t + \sum_{j=1}^{m_i} \eta_{i,j} DU_{i,j,t} + \sum_{j=1}^{m_i} \gamma_{i,j} DT_{i,j,t} \tag{18}$$

where $DU_{i,j,t} = 1$ and $DT_{i,j,t} = (t - T^b_{i,j}$ for $t > T^b_{i,j}$ and 0 otherwise, with $T^b_{i,j} = \lambda^b_{i,j} T$ denoting the timing of the jth break, $j = 1, ..., m_i$, for the ith unit, $i = 1, ..., N$, $\lambda^b_{i,j} \in \wedge$, $\wedge$ being a closed subset of (0,1). Note also that the cointegrating vector in equation (16) is specified as a function of time so that

$$\delta_{i,t} = \delta_{i,j} \ \text{for} T^c_{i,j-1} < t \leq T^c_{i,j} \tag{19}$$

with the convention that $T^c_{i,0} = 0$ and $T^c_{i,n_i+1} = T$, where $T^c_{i,j} = \lambda^c_{i,j} T$ denoting the jth time of the break,$j = 1, ..., n_i$, for the ith unit, $i = 1, ..., N$,$\lambda^c_{i,j} \in \wedge$.

The combination of the specifications given by equations (18) and (19) define six different models: Model 1 has breaks in the level, no linear trend, and a stable cointegrating vector; Model 2 has change in the level, but a stable trend and cointegrating vector; in Model 3, both the level and the trend change but the cointegrating vector does not; Model 4 has no trend, but both the cointegrating vector and the level have multiple breaks; Model 5 has a stable trend, but both the cointegrating vector and the level change; and finally, in Model 6, both the level, the trend and the cointegrating vector may change.

We assume the presence of one structural break that is common to all the countries in the panel and that is endogenously selected[21]. Under the null hypothesis of no cointegration, the $Z_j(\lambda), j = c, \tau, \gamma$ statistic where the break dates are the same for each unit is computed:

$$Z^*_j = inf(Z_j(\lambda)), j = c, \tau, \gamma \tag{20}$$

where $Z_j(\lambda)$ is the standardized statistic of the sum of the individual ADF cointegration statistics for each model, j is the break that takes places, c denotes models 1 and 4, τ models 2 and 5, and γ models 3 and 6.

We test for cointegration in all the model specifications for each group of countries and choose among them using information criteria. Subsequently, as we will see later, the

[21] In a panel, as we are interested in obtaining the estimation of the long-run relationship before and after the break, we have to impose a single common break.

selected models will be the ones employed in our empirical estimation. It is important to bear in mind that the variables employed in each group slightly differ, as we use those found to be the most robust for each country group.

The results of the tests are shown in Table 6. The Z_j^* statistic is in the third column, the fourth column presents the time of the break, and the Akaike (AIC) and the Bayesian information (BIC) criteria are in the last two columns. For each group, the model with the lowest AIC and BIC is selected, marked in bold. If two models are similar, we choose the less restrictive model, in this case, the model which allows for a change in the cointegration vector (that is, Models 4, 5 and 6). For the complete group, according to the AIC the best is Model 5, and for the BIC, Model 3. However, as Model 5 is a more complete and unrestricted model, we select it. The estimated break takes place in 2008, when the economic crisis starts. As for the EU countries, according to the AIC, Model 3 and 6 are very similar (-3.771 and -3.710). Therefore, we choose Model 6. In this case, the break occurs in 1998, a year before the launching of the euro. Concerning the EA countries, we select model 6. The break takes place in 2004, at the time of the large EU enlargement to the East. Finally, for the EA core and peripheral countries, the chosen models are 5 and 3, respectively. The change occurs in 2009 and 2010, also at the time of the crisis. The null hypothesis of no cointegration is clearly rejected, in all the models selected, at 1% of significance.

Therefore, in every model selected, the structural break takes place at important economic events, such as the launching of the euro, the EU 2004 enlargement, and the 2008 economic crisis. We include these changes in our estimation.

4.4 Slope homogeneity

Once we have chosen the model specification for each group and tested for cointegration using Banerjee and Carrion-i Silvestre (2015) methodology, we can test as well for homogeneity of the slope parameters in the models. For this purpose we use Pesaran and Yamagata (2008) test, which is a standardized dispersion version of Swamy's test of slope homogeneity, where N can be large relative to T.

Consider the panel data model with fixed effects and heterogeneous slopes:

$$y_{i,t} = \alpha_i + \beta' x_{i,t} + \varepsilon_{i,t}, \tag{21}$$

where α_i is bounded on a compact set, $x_{i,t}$ is a $k \times 1$ vector of strictly exogenous regressors, β_i is a $k \times 1$ vector of unknown slope coefficients, such that $||\beta_i||<K$.

The null hypothesis of interest is

$$H_0 : \beta_i = \beta \text{ for all } i, \tag{22}$$

against the alternative

$$H_1 : \beta_i \neq \beta_j \text{ for a non-zero fraction of pairwise slopes for } i \neq j \tag{23}$$

Swamy (1970) bases his test of slope homogeneity on the dispersion of individual slope estimates from a suitable pooled estimator.

The standardized version is called Δ test. Additionally, the small sample properties of the dispersion tests can be improved under the normally distributed errors by considering the mean and variance bias adjusted versions of $\hat{\Delta}$, called $\hat{\Delta}_{adj}$.

The results from the Pesaran and Yamagata (2008) homogeneity test are shown in Table 7. The null hypothesis of homogeneous slope is rejected at 1% significance level for both the $\hat{\Delta}$ and $\hat{\Delta}_{adj}$ tests in all country-groups. Therefore, the best options to estimate the long-run cointegration relationships are the PMG and MG estimators, instead of the pooled estimator, as they allow some of the parameters of the model to be heterogeneous. Moreover, we are also able to choose also between the PMG and MG estimators in our long-run estimation.

4.5 Empirical model estimation: Dynamic Common Correlated Effects Pooled Mean Group estimator

As we are interested in the long-run effects of a given set of variables, as well as in whether the impact of some of them is homogeneous across units, we use the PMG estimator of Pesaran et al. (1999). By homogeneous effect we mean that the effect of a variable is the same for all the units considered in a panel, as opposed to heterogeneous effect, when it differs.

Suppose that for T periods and N groups we estimate an ARDL (p, q) model of the form:

$$y_{i,t} = \alpha_i + \sum_{j=1}^{p} \lambda_{i,j} y_{i,t-j} + \sum_{j=0}^{q} \beta_{i,j} x_{i,t-j} + \varepsilon_{i,t} \tag{24}$$

where $x_{i,t}$ $(k \times 1)$ is the vector of explanatory variables (regressors) for group i, in our case, the robust determinants selected through the BMA analysis, $\lambda_{i,j}$ are the coefficients of the lagged dependent variables, and $\beta_{i,j}$ are those of the explanatory variables.

Because there is CSD in the panel, as mentioned previously, we include the cross-sectional averages of the dependent and independent variables and their two lags, following the DCCE approach of Chudik and Pesaran (2015). Moreover, we take into account the existence of structural breaks and estimate the selected models for each group of countries following the results of subsection 4.3. Thus, equation (24) can be written as:

$$y_{i,t} = \beta_{0,i} D_{i,t} + \sum_{j=1}^{p} \lambda_{i,j} y_{i,t-j} + \sum_{j=0}^{q} \beta_{i,j} x_{i,t-j} + \sum_{l=0}^{pT=2} \delta'_{i,l} \bar{z}_{t-l} + \varepsilon_{i,t} \tag{25}$$

where $D_{i,t}$ is the deterministic component in equation (18), that includes α_i, and $\bar{z}_t = (\bar{y}_{t-1}, \bar{x}_t)$ are the cross-sectional averages of the dependent and independent variables, where $pT = 2$ is their number of lags.

Equation (25) is transformed into an error correction model:

$$\Delta y_{i,t} = \phi_i [\sum_{j=1}^{p} y_{i,t-j} - \theta_{0,i} D_{i,t} - \theta_{1,i} x_{i,t}] + \sum_{j=1}^{q} \beta_{i,j} \Delta^j x_{i,t} + \sum_{l=0}^{pT} \delta'_{i,l} \bar{z}_{t-l} + \varepsilon_{i,t} \tag{26}$$

where the long-run effects, estimated by maximum likelihood, are the following:

$$\theta_{0,i} = \frac{\beta_{0,i}}{1 - \sum_{j=1}^{p} \lambda_{i,j}}, \quad \theta_{1,i} = \frac{\sum_{j=0}^{q} \beta_{i,j}}{1 - \sum_{j=1}^{p} \lambda_{i,j}} \tag{27}$$

and the error correction model (ECM) parameter is:

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{i,j}\right) \tag{28}$$

In Table 8 we present a summary of the empirical results obtained in the paper. The model estimated for each group of countries appears in the second column, and the variables in the third one. We report the information for the models selected (either 5 or 6, both including a break in the cointegration vector, with the exception of the Eurozone peripheral countries, for which model 3 is selected) and denote by "d" the variables after the shift[22]. In the next three columns, we present the coefficient homogeneity restrictions, as well as the likelihood ratio (LR) and the Hausman tests. Finally, the order of the ARDL model for the short-run variables is in the last column.

Prior to the estimation of the models, we have tested for individual long-run homogeneity of the variables in each specification. We have already tested the hypothesis of join parameter homogeneity using the Pesaran and Yamagata (2008) statistic and this was rejected. Next, we apply a different strategy to decide whether we can impose that one or more long-run parameters have common value for the elements of a country-group. For this, we use the Hausman test as well as a LR test. The Hausman (1978) test (as in Pesaran et al., 1999), compares the PMG and MG estimators. The null hypothesis is that under slope homogeneity, both the MG and PMG are consistent estimators, but the MG estimator is inefficient, whereas the opposite is true for the PMG estimator. The LR test is defined under the null hypothesis of equal long-run coefficients. We test whether all the variables or only some of them can be assumed to have equal parameters in the long-run specification. This test is more restrictive, because unlike the Hausman test (that compares the estimators), it assumes that the effect of the variables considered have the same coefficient in all the cross-section units[23].

As mentioned previously, the selection of the variables is based on the BMA analysis of Camarero et al. (2021), where a large set of potential covariates was considered (as described in Table 1). For example, 11 variables were included in the group "Market size and population" or 13 in "Labour market" for labor costs and productivity. Using cointegration techniques in panels, we selected the variables from the group of robust covariates, which may differ depending on the group of countries analyzed. We have found that there is at least one long-run coefficient common to all its members (homogeneous parameter) in every country group. Moreover, we find that the degree of homogeneity has increased over time, as in half of the cases, the homogeneous variable is the one after the break or it is

[22]The list of variables and abbreviations can be found in Table 2.

[23]Evidently, the larger is the number of cross-section units, the higher the potential degree of heterogeity. Pesaran et al. (1999) mention that, in the case of cross-country studies, the likelihood ratio test usually reject the hypothesis of equal error variances and/or slopes (short-run or long-run) at conventional significance levels.

only significant in the second part of the sample. This result can be taken as evidence of growing economic interdependence, not only among EU or Eurozone countries but also in the rest of the world. As our variable of interest is the US outward FDI, the interpretation is that American FDI is attracted by some variables with similar intensity, and this can be related to important events that have affected FDI with origin in the US. This is the case of the launching of the euro, the 2004 EU enlargement, or the 2008 financial crisis.

For the full group of (54) countries, we assume that the variable **trade openness** or $trdo_t$ is homogeneous. According to the Hausman test, the hypothesis that attributes the common slope to this variable cannot be rejected, so the PMG estimator is preferred over the MG estimator. However, this specification does not fulfill the LR test's condition, which is more strict. In such a large panel of data with countries from different continents, there is a large degree of heterogeneity. Concerning the EU countries, the variable found to have a common effect across countries is **revenue from taxes after the break** or $drtrd_t$. Also in this case, while the hypothesis of common slope cannot be rejected, the null of the LR test is rejected again. Once we move to smaller and more homogeneous groups, as is the case of the EA, core, and peripheral countries, the null hypothesis of equal long-run coefficients is not rejected. Regarding the Eurozone group, **labour compensation after the break** or $dlabc_t$ is homogeneous. As for the EA core countries, we find two possible models, Model 5a, where both openness and labor compensation can be restricted to be the same across countries, and Model 5b, where **trade openness** ($trdo_t$) and this same variable after the break ($dtrdo_t$) have a common slope. Finally, in the case of the periphery, the **mean tariff rate** or $mtrt_t$ is the homogeneous variable.

Once we have enumerated the long-run variables that are estimated as homogeneous for all the countries in the different groups, we will analyze and interpret the role of the variables in the long-run relationships. Concerning the estimation of the coefficients, the difference between the two approaches (PMG and MG) is that for those variables for which the homogeneity restriction cannot be accepted, the coefficient is the average of the individual coefficients. The results of the panel estimation is presented in Table 9, where the homogeneous long-run coefficients are marked in bold. Therefore, for example, in the second column of the Table, where we include the estimation of Model 5 for the 54 countries, only **trade openness** is homogeneous and appears in bold. The remaining long-run parameters are the averages of the 54 units in the group. In this first case, **trade openness** is significant both before and after the break. In addition, the Table includes the error correction cointegration test (based on the significance of the error correction parameter) and the short-run coefficients for each of the models. The variables after the break are below the dashed lines. We start the analysis of the estimation results with the long-run coefficients by group of variables.

Concerning the long-run coefficients, the only variable that was found a robust covariate in all the country groups is **GDP** or $lgdp_t$. In all the groups the parameter is positive when it is significant, as in the cases of the Eurozone core countries and the full group. This sign is consistent with HFDI, where market size plays an important role attracting foreign investment. On the other hand, the parameter after the break $dlgdp_t$ is negative for the EU countries. Since the break takes place in 1998, this would imply that, after the launching of the euro, the US strategy may have changed from HFDI to VFDI, an effect probably related to international Global Value Chains (GVCs). Sondermann and Vansteenkiste (2019) obtained similar results concerning the impact of the euro on the drivers of FDI.

A second group of variables contains those related to the labor market. Depending on the group of countries, three different proxies for labour costs were found to be robust: **population density** or $lpod_t$, **total factor productivity** or tfp_t, and **labour compensation** or $labc_t$. In Table 9, **population density** ($lpod_t$), taken as a proxy for the labor endowment of the host country, was found to be a robust determinant in the model including all the countries. This variable is significant at 5%, has a negative sign before the break, and becomes non-significant afterward. In principle, higher population density may attract a concentration of firms looking for abundant and cheaper labor. Consequently, the competition effect could offset the positive spillovers arising from a common pool of resources, deterring the entry of new firms[24]. The sign of this same variable is positive for the EA peripheral countries, implying that US MNCs have been attracted by an abundant and probably, less expensive workforce, an impact compatible with VFDI. To this same effect point the results of **labor compensation** ($labc_t$) in the Eurozone and core countries: the sign is negative so that lower salaries would attract FDI. However, the effect is positive in the Eurozone after the break, which took place in 2004, and reduces the negative impact of the original variable. A plausible hypothesis for this impact could be that with the expansion of the EU to the Eastern countries, US multinational companies (MNCs) have been giving preeminence to the more

[24]For more information about competition forces and FDI location, see Crozet et al. (2004).

productive and skilled workers in the core instead of mere labor cost considerations. This strategy is compatible with intra-industry VFDI, where firms are generally located in high-skill countries and sectors that also produce high-skill inputs involving products that are at some stages close to the parent firm's final stage of production (Alfaro and Charlton, 2009). Therefore, after the 2004 EU enlargement, there has probably been relocation and redistribution of US MNCs activities within the EA. While intra-industry VFDI has been mainly established in the "old" members of the Eurozone, where there is a higher proportion of skilled workers, pure VFDI has prevailed in the Center and East, where labor costs are lower.

Regarding the covariates related with trade, we have used three proxies that were robust in the previous BMA analysis for the five groupings considered: **trade openness** ($trdo_t$), **revenue from trade taxes** or $rtrd_t$ and **mean tariff rate** or $mtrt_t$. The first one, **trade openness**, is significant at 1% and has a positive sign in the case of the largest group. Specifically, a one-unit increase rises US OFDI by 0.5%. This effect is compatible with VFDI, where trade and FDI are complements and mostly consist of trade in intermediate goods across affiliate firms. Similar results are found for the EA core countries. However, in this case, this coefficient changes sign after the break in the cointegration vector and even offsets the magnitude of our original variable. As the break occurred in 2008, it would imply that HFDI strategies have prevailed after the crisis. A possible explanation could be the important role played by large economies on American investment even after the economic downturn, where most US OFDI is aimed at supplying the local markets, such as those in Great Britain, Canada, Australia, and China. Nonetheless, this is not the case in the core countries, where the variable after the break $dtrdo_t$ remains positive. Regarding the EU countries, the **revenue from tariffs** or $rtrd_t$ has a negative sign[25]. Since this variable can be interpreted as an increase in trade costs, its sign implies VFDI. After the break in 1998, $drtrd_t$ remains significant but positive and more than compensates the magnitude of the coefficient of the original variable, meaning that with the introduction of the euro, a more horizontally-oriented FDI strategy may have prevailed in the EU countries. Concerning the Eurozone peripheral countries, the **mean tariff rate** or $mtrt_t$ that is a robust determinant in the Eurozone peripheral countries, has a negative sign, also pointing towards VFDI during

[25]In particular, one unit increase in the tariff reduces US OFDI by approximately 85%. The possible explanation for this large effect is that revenue trade taxes is meager (between 0.5% and 1.5%) for the fundamentally open EU countries. Therefore, a 1 percentage point increase of this variable implies a doubling of the tariff.

the whole sample[26]. Finally, for the Eurozone countries (third column in Table 9), increases in the mean tariff rate ($mtrt_t$) imply more US FDI, intended at jumping the barriers.

In the center of Table 9 we have included the value of the Error Correction Model (ECM) parameter for each of the models estimated for the country groups. Testing for the null hypothesis of no cointegration based on the significance of the error correction coefficient has been applied not only in the context of time series but also in panels (see Banerjee et al. (1998) and Westerlund (2007), respectively). In our case, all the specifications have a very signifincant ECM parameter, with the right sign and magnitude. Therefore, the null hypothesis of no cointegration is clearly rejected in all instances.

Finally, the lower part of Table 9 includes the estimated short-run coefficients for all the country groups. All of them are heterogeneous across groups. The ARDL order is shown in the last column of Table 8. We have selected the number of lags taking into account the degrees of freedom limits, but ensuring that the residuals estimated models pass the misspecification tests. The results are similar to those obtained for the long-run coefficients. $lgdp_t$ and its lag are positive when significant, which is compatible with HFDI. On the other hand, in the case of the EU countries, it turns negative after the break, implying that with the introduction of the euro, more vertical strategies are undertaken by the US companies. Concerning labor market covariates, $lpop_t$ is negative for the whole sample, but it is positive in the case of the EA periphery, an impact compatible with VFDI. Similarly, the sign of $labc_t$ is negative for the EA and core countries but positive after the break, indicating that intra-industry VFDI strategies have gained importance in the Eurozone with the EU enlargement to the East. Lastly, as for trade variables, the parameter of $trdo_t$ has a positive sign for the large group and EA core countries, implying VFDI strategies. However, the sign of $dtro_t$ is negative for the whole group (HFDI) but positive for the core (VFDI). As for the EU countries, the short-run parameter of $rtrd_t$ is negative and significant, evidence favoring VFDI. A similar response can be attributed to $mtrt_t$ in the EA periphery, although the lag of this variable is positive. The latter also happens when we analyze the post-break short-run adjustment of $drtrd_t$ for the EU and the one of $mtrt_t$ for the EA.

To sum up, our overall results show that once we analyze the short-run and long-run US OFDI determinants, both HFDI and VFDI strategies coexist for all country groups. This

[26]In this case, we find a break in the mean and the trend of the relationship, but the cointegration vector is stable during the sample period.

feature is consistent with the knowledge capital model of Markusen and Maskus (2002), where both types of strategies can be present simultaneously. Concerning the structural breaks, in the largest, more diverse group, including the 54 most important destinations of US FDI, the changes in strategy occurred after the financial crisis. However, for the EU countries, the relevant time of break is the euro's inception, and for Eurozone, the enlargement to the East. In the smaller, more homogeneous groups, the results show the importance of VFDI strategies.

5 Conclusions

The EU and the US are the two largest FDI investors and recipients. In the case of the EU, the establishment of the Single Market in 1993 and the introduction of the euro in 1999 have been powerful FDI attractors from both EU and non-EU members. In this paper, we analyze the long-run determinants of outward US FDI, from 1985 to 2019, in a large group of 54 countries from all the continents, representing over 70% of the total US outward stock in 2019. The deep trade and investment linkages between the US and the EU make it especially relevant to know the long-run motivations of US FDI in these countries. For this reason, we analyze the EU and the EA, and, within the EA, we distinguish between core and peripheral countries.

We contribute to the empirical literature in several respects: we aim to capture long-run relationships based on variable selection and testing for homogeneity restrictions instead of imposing them. We use efficient econometric techniques to work with panels where the time dimension is sometimes larger than the cross-section dimension. For this reason, we use a panel cointegration approach and estimate error correction mechanisms, allowing for flexible dynamics. Moreover, we also account for CSD, which we expect due to the simultaneous processes of globalization and European integration during our sample period. Also related to the large T-dimension of the sample, we test for the existence of structural breaks not only in the variables but also in the long-run relationships. We include these changes in the specification and estimation of models of FDI determination for five groups of countries. As one of the primary motivations of this paper is the search for common patterns across country groups, we combine the Chudik and Pesaran (2015) and Pesaran et al. (1999) approaches and use the DCCEPMG estimator allowing for one structural break. Additionally, instead of just focusing on a predetermined group of variables, we start from the variables found to be robust on Camarero et al. (2021) using BMA analysis.

The complexity of the international economic linkages makes studying the factors that attract FDI to a particular area difficult. Therefore, we have adopted an approach that tackles this complexity using methods based on careful specifications and testing plans. We have confirmed the existence of a high degree of CSD and many sources of heterogeneity in the investment strategies that cannot be captured unless we use a flexible methodology. We find cointegration in all the country groups. However, none of the long-run relationships are stable during the sample period. The world financial crisis is found to be the most important common structural break for the whole group as well as for the core and the periphery of the Eurozone. Capital mobility was profoundly affected by the financial turmoil, although MNCs' adoption of new strategies is more associated with institutional changes. Such is the case of the EU, as the break is found at the creation of the euro, as well as in the Eurozone, with the 2004 enlargement.

Our main results show that once we study the short-run and long-run determinants of US OFDI, we find both HFDI and VFDI strategies in all country groups. Nonetheless, as we move towards more homogeneous groups, the results show more intense VFDI. Moreover, some determinants have a homogeneous long-run effect on US OFDI that, as expected, becomes evident when we analyze smaller and more homogeneous groups. This is the case for the EA and the core and the periphery groups.

In the case of the three larger country groups, the US changes its FDI strategies after the structural breaks. First, in the full group of countries, the variable trade openness has a positive and homogeneous coefficient, but a negative and heterogeneous one after the 2008 crisis. In this case, the change is from VFDI to HFDI in the overall model, or it may also be the case of US FDI simply moving from some countries to others depending on its financial or macroeconomic stability. Second, a similar effect is found in the case of US FDI in the EU countries: after the inception of the euro, the trade variable (in this case, revenue from trade taxes) changes from negative (more trade protection deters FDI) to positive and homogeneous. Third, in the group of the Eurozone countries, we find a reduction in the negative sign in the labour market parameter after the 2004 enlargement. From an initial strategy based on VFDI (or low labor costs) until 2004, US firms changed to sought high-skilled labor countries in the "old" EA members in the aftermath. Indeed, while the sign of population density in EA peripheral countries is positive for the whole sample period, associated with abundant cheap labor, this factor is not enough to attract the US FDI.

From an economic policy point of view, the EU countries have maintained their attractiveness for US FDI through the sample period. Serving a large and expanding market with each enlargement and avoiding the non-tariff barriers that separate the US and the EU has always been a reason for the presence of American MNCs in Europe. In addition, the participation in GVCs, both of European and non-European ownership, has grown in the last 30 years thanks to the skill level of the labor force in the European continent and relatively low salaries in Eastern and peripheral countries. Moreover, the macroeconomic stability and the institutional quality of the EU are the bases for continuing the solid bilateral FDI relationship between the EU and the US. The international context also favors strengthening this link, as the two economic areas are interested in reducing their dependence on Asian producers. In the subsequent years, European regional value chains are expected to grow as the production of electronic components and other strategic elements of manufacturing production chains come back to Europe, probably with important US participation.

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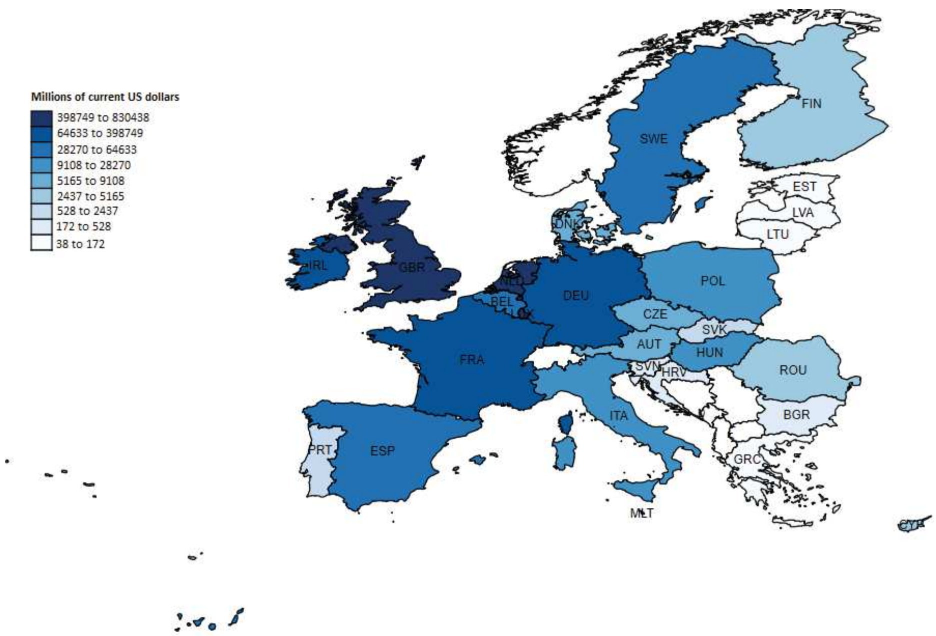
Figure 1: US OFDI stock distribution in the EU in 2019



Source: Own elaboration. Data obtained from Bureau of Economic Analysis (BEA).

Table 1: Variables selected as robust determinants of US FDI. Results of the BMA analysis in Camarero et al. (2021)

Variables	Whole group	EU countries	EA countries	EA core	EA periphery
Economic and monetary integration					
Euro	X	X	X		X
EconomicIntegration		X	X	X	X
Market size and population					
LogRealGDP	X	X	X	X	X
Euro*LogRealGDP	X	X	X		X
UrbanPopulation	X			X	X
Euro*UrbanPopulation	X				
LogSumRealGDP	X	X			
LogRealGDPdiff	X				
RealGDPgrowth	X				
LogRealMarketPotential	X				
LogSpatialLagUSFDI	X	X		X	
LifeExpectancy					
OldDependencyRatio			X		
Labour market					
SkillLevel			X		
Euro*SkillLevel			X		
HCI		X	X		
Euro*HCI					
LogPopulationDensity	X	X	X		X
Euro*LogPopulationDensity	X	X	X		X
EducLevel					
SkillLeveldiff		X			
EducLeveldiff	X				
LogRealGDPdiff*SkillLeveldiff					
LogRealGDPdiff*EducLeveldiff	X				
LabourCompensation			X	X[a]	
TFP	X	X			
Trade and international openness					
TradeOpenness	X			X	
Euro*TradeOpenness	X				
MeanTariffRate			X		X
Euro*MeanTariffRate			X		X
FTA					
DepthFTA					
RevenueTradeTaxes	X	X			
KOFSoGIdf	X				

NOTES: The selected variables are market in red. [a]In Camarero et al. (2021) we do not find robust determinant in the group "labour market" for the EA core countries. Therefore, we choose the variable with the largest PIP in this group, which is *LabourCompensation*.

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Table 2: Variables and definitions

Variable	Short abbreviation	Definition	Source
Dependent variable			
US outward FDI stock	lusfdi	Outward FDI stock from the United States to the host country at current U.S. dollars.	BEA
Market size and population			
LogRealGDP	lgdp	Logarithm of the host country's real GDP at constant 2010 US dollars	WDI from Wold Bank and WEO from IMF
Labour market			
LogPopulationDensity	lpod	Logarithm of the population density of the host country	WDI from World Bank
TFP	tfp	Total factor productivity of the host country at constant national prices (2017=100)	Penn World Table 9.1
LabourCompensation	labc	Share of labour compensation in GDP of of the host country at current national prices	Penn World Table 9.1
Trade openness			
TradeOpenness	trdo	Total imports and exports of the host country divided by total GDP at current US dollars	WDI from World Bank
RevenueTradeTaxes	rtrd	Revenue from trade taxes (% of trade sector) of the host country.	Fraser Institute
MeanTariffRate	mtrt	Mean tariff rate of the host country imposed to product imports	Fraser Institute

NOTES: BEA=Bureau of Economic Analysis, WDI=World Development Indicators, WEO=World Economic Outlook, IMF=International Monetary Fund.

Table 3: Groups of countries

Groups of countries	Countries included	Number of countries
Whole group	Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, China, Colombia, Costa Rica, Cyprus, Denmark, Dominican Republic, Ecuador, Egypt, Finland, France, Germany, Greece, Guatemala, Honduras, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Kenya, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nicaragua, Norway, Panama, Paraguay, Peru, Philippines, Portugal, Republic of Korea, Romania, Senegal, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, United Kingdom, and Uruguay	54
EU countries	Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Romania, Spain, Sweden and United Kingdom.	16
EA countries	Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain.	11
EA core	Austria, Belgium, France, Germany and Netherlands.	5
EA periphery	Finland, Greece, Ireland, Italy, Portugal and Spain.	6

NOTES: We exclude from our sample the micro-states where US MNCs invests largely. The reason is that most FDI to these countries is not reflecting decisions based on long-run factors. A large proportion of these FDI outflows are just flows going in and out of the country on their way to their final destination, with this stop due to the favorable corporate tax conditions of the host country (see Blanchard and Acalin (2016)). These are the cases of Antigua and Barbuda, Bahamas, Barbados, Bermuda, Fiji, Grenada, Hong Kong, Luxembourg, Mauritius, Singapore and Trinidad and Tobago.

Table 4: Tests for CSD

			$lusofdi_t$	$lgdp_t$	$lpod_t$	tfp_t	$labc_t$	$trdo_t$	$rtrd_t$	$mtrt_t$
Pesaran (2004) test	P	0	17.10***	43.08***	9.18***	25.82***	10.23***	60.56***	21.76***	41.38***
		1	16.35***	47.42***	4.19***	26.04***	11.04***	62.38***	23.69***	36.38***
		2	15.26***	46.5***	4.41***	26.25***	10.29***	62.1***	24.78***	35.24***
Pesaran 2015 test			162.54***	204.18***	190.56***	29.90***	15.48***	75.94***	54.69***	140.12***

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. The critical values of both CSD tests are 2.57, 1.96 and 1.64 at significance levels 1%, 5% and 10%, respectively. P is the number of lags for each variable.

Table 5: Panel unit root tests (1985-2019)

			$lusofdi_t$	$lgdp_t$	$lpod_t$	tfp_t	$labc_t$	$trdo_t$	$rtrd_t$	$mtrt_t$
Pesaran (2007) test	P	0	-2.71**	-1.986	-1.642	-2.185	-2.425	-1.983	-2.003	-2.579*
		1	-2.551*	-2.513	-4.684***	-2.342	-2.581*	-2.248	-2.14	-2.604*
		2	-2.591*	-2.267	-2.324	-2.203	-2.165	-2.088	-2.249	-2.183
Bai and Carrión-i Silvestre (2009) test		Pm^*	0.059	1.036	-0.900	0.611	0.213	-0.332	0.112	-0.848
		P^*	108.86	123.22	94.77	116.98	111.13	103.12	109.65	95.534

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. (1) The critical values of the Pesaran (2007) CIPS test are -2.73, -2.61 and -2.54 at 1%, 5% and 10% significance level, respectively. P is the number of lags for each variable. (2) Concerning the Bai and Carrion-i Silvestre (2009) test, the Z^* and Pm^* statistics follow a normal distribution and their 1%, 5% and 10% critical values are 2.326, 1.645 and 1.282, respectively. P^* follows a Chi-squared distribution with n (breaks+1) degrees of freedom and its critical values are 145.10, 133.26 and 127.21 at 1%, 5% and 10%, respectively.

Table 6: Banerjee and Carrion-i Silvestre (2015) panel cointegration test (1985-2019)

Groups of countries	Models	Z_j^*	Estimated break point	AIC	BIC
Whole group	Model 1	-10.851***	10 (1996)	-0.135	0.696
	Model 2	-8.032***	14 (2000)	-1.910	-0.913
	Model 3	-5.927***	26 (2012)	-2.405	-1.241
	Model 4	-13.108***	19 (2005)	-0.325	1.004
	Model 5	**-12.525*** **	**22 (2008)**	**-2.520**	**-1.027**
	Model 6	-8.660***	25 (2011)	-2.225	-0.563
EU countries	Model 1	-4.768***	25 (2011)	-2.797	-2.150
	Model 2	-4.940***	10 (1996)	-3.467	-2.691
	Model 3	-5.549***	26 (2012)	-3.771	-2.865
	Model 4	-7.017***	12 (1998)	-2.669	-1.634
	Model 5	-8.140***	19 (2005)	-3.555	-2.391
	Model 6	**-5.325*** **	**12 (1998)**	**-3.710**	**-2.416**
EA countries	Model 1	-8.414***	22 (2008)	-3.371	-2.78
	Model 2	-7.986***	10 (1996)	-3.781	-3.073
	Model 3	-11.035***	27 (2013)	-4.228	-3.402
	Model 4	-3.158***	22 (2008)	-3.484	-2.540
	Model 5	-8.008***	10 (1996)	-4.292	-3.230
	Model 6	**-8.081*** **	**18 (2004)**	**-4.652**	**-3.472**
EA core countries	Model 1	-0.428	21 (2007)	-4.166	-3.695
	Model 2	-8.836***	23 (2009)	-6.131	-5.567
	Model 3	-17.333***	23 (2009)	-6.464	-5.805
	Model 4	-2.345**	6 (1992)	-5.205	-4.452
	Model 5	**-23.027*** **	**23 (2009)**	**-6.416**	**-5.569**
	Model 6	-13.603***	26 (2012)	-6.113	-5.172
EA peripheral countries	Model 1	-1.008	18 (2004)	-3.300	-2.801
	Model 2	-21.691***	24 (2010)	-6.162	-5.564
	Model 3	**-32.362*** **	**24 (2010)**	**-6.277**	**-5.580**
	Model 4	-9.071***	22 (2008)	-4.656	-3.858
	Model 5	-13.542***	24 (2010)	-5.231	-4.334
	Model 6	-16.301***	26 (2012)	-5.975	-4.980

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. Critical values of Z_j^* are -2.824,-2.113 and -1.759 at 1%, 5% and 10% significance levels, respectively, for the model with constant; -2.924,-2.240 and -1.835 are their equivalents in the model with trend. AIC= Akaike Information Criterion, BIC=Bayesian Information Criterion. The selected models are marked in bold.

Table 7: Pesaran and Yamagata (2008) slope homogeneity test

Groups of countries	Models	$\hat{\Delta}$	$\hat{\Delta}_{adj}$
Whole group	Model 5	35.750***	41.073***
EU countries	Model 6	15.564***	17.882***
EA countries	Model 6	13.337***	15.323***
EA core countries	Model 5	6.731***	7.733***
EA peripheral countries	Model 3	6.439***	6.990***

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10% , respectively. The critical values are 2.57, 1.96 and 1.64 at 1%, 5% and 10% significance level, respectively.

Table 8: Models summary

(a)

Groups of countries	Models	Variables	Coefficient homogeneity restrictions
Whole group	Model 5	lusofdi lgdp lpod trdo dlgd dlpod dtrdo	N.A. $\neq^{*} \neq^{**} = \forall^{***} \neq \neq \neq^{**}$
EU countries	Model 6	lusofdi lgdp tfp rtrd dlgdp dtfp drtd	N.A. $\neq \neq \neq^{**} \neq^{*} \neq = \forall^{***}$
EA countries	Model 6	lusofdi lgdp labc mtrt dlgdp dlabc dmtrt	N.A. $\neq \neq^{**} \neq^{*} \neq = \forall^{***} \neq$
EA core	Model 5a	lusofdi lgdp labc trdo dlgdp dlabc dtrdo	N.A. $\neq^{**} = \forall^{*} = \forall^{***} \neq \neq \neq$
	Model 5b	lusofdi lgdp labc trdo dlgdp dlabc dtrdo	N.A. $\neq^{**} \neq = \forall^{**} \neq \neq = \forall^{*}$
EA periphery	Model 3	lusofdi lgdp lpod mtrt	N.A. $\neq \neq^{**} = \forall^{*}$

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. The signs $= \forall$ and $\neq$ denote homogeneity and heterogeneity of the estimated parameters, respectively. N.A. = not applicable.

(b)

Groups of countries	Models	Hausman test	LR test	ARDL order
Whole group	Model 5	0.04 (0.85)	332.44 (0.000)	1000100
EU countries	Model 6	2.26 (0.13)	36.405 (0.002)	1001000
EA countries	Model 6	1.90 (0.17)	15.194 (0.125)	1100000
EA core	Model 5a	2.96 (0.23)	12.647 (0.125)	1001001
	Model 5b	5.30 (0.07)	14.058 (0.080)	1000110
EA periphery	Model 3	2.21 (0.14)	8.249 (0.1430)	1101

Table 9: Panel estimation of the dynamic model (DCCEPMG) for all the country groups

	Whole group	**EU countries**	**EA countries**	**EA core**		**EA periphery**
Dependent variable $lusofdi_t$	**Model 5**	**Model 6**	**Model 6**	**Model 5a**	**Model 5b**	**Model 3**
Structural break	2008	1998	2004	2009	2009	2010
Long run coefficients						
$lgdp_t$	1.169*	2.215	2.588	9.167**	8.287**	-1.036
$lpod_t$	-4.622**					8.000**
tfp_t		-0.018				
$labc_t$			-0.049**	**-0.030***	-0.005	
$trdo_t$	**0.005*****			**0.028*****	**0.015****	
$rtrd_t$		-0.854**				
$mtrt_t$			0.072*			**-0.123***
$dlgdp_t$	1.680	-0.950*	0.325	0.049	0.431	
$dlpod_t$	-2.929					
$dtfp_t$		0.023				
$dlabc_t$			**0.038*****	-0.082	-0.042	
$dtrdo_t$	-0.020**			-0.002	**0.015***	
$drtrd_t$		**1.123*****				
$dmtrt_t$			-0.056			
$ecm_t - 1$	-0.837***	-0.689***	-0.710***	-0.538**	-0.632***	-0.535***
Short run coefficients						
$\Delta lgdp_t$	0.981*	1.144	2.222*	3.934***	3.834**	-0.132
$\Delta lgdp_t - 1$			1.801			2.547***
$\Delta lpod_t$	-3.714***					4.237**
Δtfp_t		0.001				
$\Delta labc_t$			-0.027*	-0.016***	-0.014	
$\Delta trdo_t$	0.004***			0.015***	0.009***	
$\Delta trdo_t - 1$				-0.018		
$\Delta rtrd_t$		-0.492***				
$\Delta rtrd_t - 1$		-0.202				

	Whole group	EU countries	EA countries	EA core		EA periphery
Dependent variable	**Model 5**	**Model 6**	**Model 6**	**Model 5a**	**Model 5b**	**Model 3**
lusofdi$_t$						
Structural break	2008	1998	2004	2009	2009	2010
$\Delta mtrt_t$			0.045**			-0.066***
$\Delta mtrt_t - 1$						0.073***
$\Delta dlgdp_t$	0.519	-0.555**	0.025	0.011	0.082	
$\Delta dlgdp_t - 1$	-0.195				-0.261	
$\Delta dlpod_t$	-0.446					
$\Delta dtfp_t$		0.020				
$\Delta dlabc_t$			0.027***	0.081	0.045	
$\Delta dlabc_t - 1$					-0.012	
$\Delta dtrdo_t$	-0.016***			0.003	0.010***	
$\Delta dtrdo_t - 1$				0.009		
$\Delta drtrd_t$		0.773***				
$\Delta dmtrt_t$			-0.031			
N ° of observations	1782	528	363	165	165	198

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. The homogeneous parameters are marked in bold.